ISSN 0511-5728
The West Indian Journal of Engineering
Vol.33, Nos.1/2, January 2011, pp.26-33

Reliability Evaluation for the Assessment of Wind Energy Penetration in Power Systems

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(Received 19 January 2006; Accepted January 2011)

Abstract: *Wind energy is rapidly becoming an important source of electrical generation. Decisions about the viability of using wind energy in combination with conventional energy sources should be determined on their reliability to meet a load demand and the cost of using such a combination. This paper presents a reliability evaluation method that comprises three main aspects: wind data modelling, wind turbine generator power evaluation and a system adequacy assessment. To determine the reliability of a given wind penetration, Monte-Carlo techniques have been used based on random combinations of conditions for hourly wind speed, conventional generation availability and load. Results are presented as probabilistic indices. The method is implemented using a computer program, and a case study of an electrical system representative of a small country or island is presented.*

Keywords: *Autoregressive, Wind generation, Well-being analysis, Reliability, WTG*

1. Introduction

Wind generation is being increasingly utilised in electric power systems due primarily to its low cost of installation and straightforward operation and maintenance. In addition to this, the use of renewable energy facilitates reductions in greenhouse gas emissions and environmental risks associated with conventional energy generation. As a result, over the last few years, new installations of wind generation worldwide have grown enormously with the size of wind farms and the Wind Turbine Generators (WTGs) increasing steadily. In this context utilities around the globe are studying ways to evaluate its impact on the electrical system and especially to determine the maximum acceptable degree of penetration in the generation mix. Generation expansion studies are typically carried out by utilities using reliability assessment. A similar approach can be used when wind generation is included in the system. However, the stochastic nature of the wind regime and therefore, the power delivered by the WTGs require a more sophisticated analysis that takes into account this additional factor.

This paper introduces a reliability evaluation method that comprises three main aspects: wind data modelling, wind turbine generator power evaluation and a system adequacy assessment. The general method is based on the work of Billinton and Karki (2004), but several changes have been made, especially with respect to the wind data modelling, the representation of the WTG power curve and the Monte-Carlo Simulation (MCS). Comparative examples are shown in this paper to validate the use of these new approaches. For the calculation of the wind data modelling actual hourly wind speed data at a specific location is represented by an Auto-Regressive (AR) model. Using this AR model, hourly wind speed can be generated for any number of simulated years for use in the adequacy assessment. The possible power generated by the WTGs at the candidate site is calculated based on the generated hourly wind speed. This wind power figure is combined with information on conventional plant availability and power from other existing units (wind and/or conventional) connected to the power grid, and the load in the system.

By comparing the available capacity with the demand, it is possible to establish the capability of the system to serve the load. To determine the reliability of a given wind penetration, a large number of simulations is performed according to standard Monte-Carlo method based on random combinations of conditions of wind, load and conventional plant availability. Finally, probabilistic indices are determined to help to assess the reliability of the system. The implementation of the method using a computer program in Matlab is illustrated. The illustrative example is an electrical system typical of a small island system supplied by conventional diesel generation.

2. The Reliability Evaluation

The reliability evaluation method is based on the assessment of the available amount of power generation at a given hour and its comparison with the load demand at that time. This calculation is repeated for a large number of hours (usually over several years) using randomly generated values of generation and load. From these simulations a series of probabilistic indices and factors are calculated. Figure 1 shows a simplified block diagram that identifies the main steps on the general calculation process.

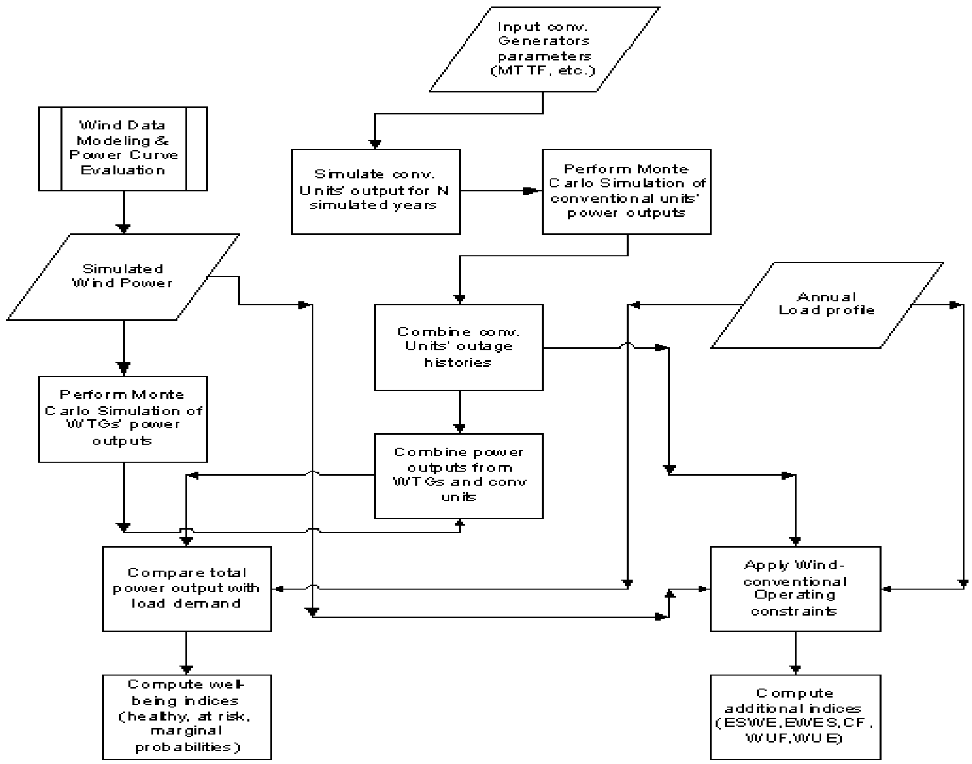

Figure 1. Simplified block diagram of the reliability evaluation

2.1 Wind Speed Simulation

The reliability analysis requires wind data over a large number of years. For short-term forecasting (time span of minutes and hours) of wind regime, one of the common methods used is Autoregressive Moving Average (ARMA) modelling. Billinton and associates (Billinton et al., 1996; Billinton and Karki, 2004) described the use of ARMA modelling for the generation of long-term wind data and established that very accurate results can be achieved. A subset of ARMA models is the so-called autoregressive, or AR models. An AR model expresses a time series as a linear combination of its past values plus a noise term. The order of the AR model tells how many different past values are included. The use of AR models is common because of their simple implementation.

The method implemented in this paper is an AR model that uses the algorithm proposed by Neumaier (Neumaier, 2001), which computes the model coefficients and evaluated criteria for the selection of the model order stepwise for successively decreasing order AR models. The resulting AR model was tested by evaluating its residuals and correlations. The output of the AR model is a time series of hourly wind speeds for as many years as required by the study specifications. The AR model generates this time series based parameters determined from actual measured wind data. This wind data is normally measured at some standard height, usually 10m. In most cases, the measured wind speed height is not the appropriate for calculation purposes relating to the operation of the WTGs. It is necessary to correct the wind speeds to the particular WTG hub height. This is accomplished by using the Justus' formula (Ehnberg, 2003).

2.2 Wind Turbine Generator Power Evaluation

The power curve was modelled following the one used by Billinton and Karki (2004) and shown in Figure 2. Ehnberg (2003) described the power curve of a WTG by a series of general equations. Since Ehnberg's model produced a power curve similar to that produced by Billinton and Karki (2004), the power curve equations were adopted to model the WTG power curve. Figures 2 and 3 show a comparison of the WTG power curves used by Billinton and Karki (2004) and Ehnberg (2003), respectively.

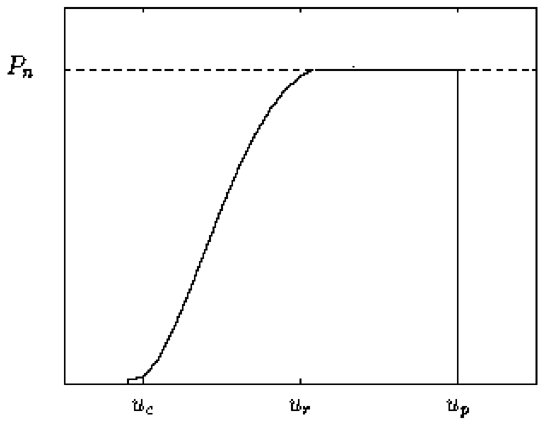

Figure 2. WTG Power Curves used by Billinton and Karki (2004)

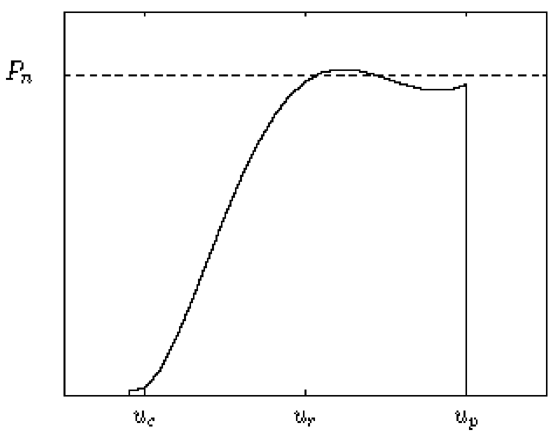

Figure 3. WTG Power Curves used by and Ehnberg (2003)

By observing the two power curves, particular properties were noted. The region between the cut-in wind speed and the rated wind speed is similar to each other. After the rated wind speed the differences between the curves become more apparent, where Ehnberg (2003)'s power curve experiences an overshoot, and oscillatory type effect, whereas Billinton and Karki (2004)'s curve becomes a constant value following the rated wind speed.

There are 3 defined ranges in the Ehnberg model as opposed to the 4 defined ranges of the Billinton and Karki model. In order to use the Ehnberg mathematical model to implement the Billinton and Karki model, the mid-range equation from the Ehnberg model was used where the coefficients A to F were solved using the WTG parameters. The range for the equation was then redefined to be 'cut-in wind speed ≤ v < rated wind speed'. Thus the mathematical model for the WTG power was given by,

$$P = \left\{ \begin{array}{l} 0,\ v < u_c \\ A_1v^5 + B_1v^4 + C_1v^3 + D_1v^2 + E_1v + F_1,\ u_c \le v < u_r \\ P_r,\ u_r \le v < u_{co} \\ 0,\ v \ge u_{co} \end{array} \right\} \quad (1)$$

where v is any positive real wind speed, and A_1 to F_1 are the coefficients for a specified WTG.

By using the WTG parameters for a particular turbine - such as cut-in wind speed, rated power, etc. – is possible to calculate the coefficients to represent the power curve with the previous set of equations. Once these were known, the simulated wind speed values can be translated in power outputs.

2.3 System Adequacy Assessment

2.3.1 Monte Carlo Simulation (MCS)

Billinton and Karki (1999) stated that Monte-Carlo Simulation could be used to estimate the reliability indices. MCS should include system effects, but that this may not be possible without excessive approximation in a direct analytical approach. Another disadvantage of using analytical techniques was that they did not produce distributions associated with the various indices, which is easily generated by MCS.

For the purpose of analysing the system adequacy with the inclusion of wind generation there are two different aspects that require MCS:

1) The wind speed is a stochastic variable and as such its simulation must include a random component that allows for the AR model to generate variable series of wind speed for different years. This variability of the wind regime was accomplished by using a method developed by Neumaier and Schneider (2001). This technique incorporates a MCS on the AR model by using Gaussian pseudo-random vectors with a specific covariance matrix instead of the noise vectors.
2) The generation model in terms of the random availability of the different units in the system (wind and conventional). This MCS was modelled by using the methods described by Billinton and Karki, (1999) and which is based on the Mean Time to Derate (MTTD), Mean Time to Derate Repair (MTDR), Mean Time to Failure (MTF) and Mean Time to Repair (MTTR) of each generator.

For the generation model, it was assumed that the generating unit (wind or conventional) was in one of 3 states: fully available, partially available, or unavailable. Billinton and Karki, 1999, 2004) assumed that generating unit up, partially available and down residence times were exponentially distributed (Billinton, 1970). Billinton and Karki (2004) defined the residence times using the following equations,

$$UpTime = Min(-MTTF * \ln X_1, -MTTD * \ln X_2) \quad (2)$$

$$DownTime = -MTTR * \ln X_3 \quad (3)$$

$$DeratedTime = -MTDR * \ln X_4 \quad (4)$$

With (i = $_{1, 2, 3, 4}$) random numbers between 0 and 1.

Based on the residence times the outage history for each unit was calculated. This history can be represented graphically as shown in Figure 4. In order to determine the outage history of a generating unit in the simulation technique, the smaller of the MTTF and MTTD was chosen as the uptime, and the unit downtime was the corresponding MTTR or MTDR, respectively. The outage history of the total capacity can then be determined by combining the outage histories of all the generating units in the system.

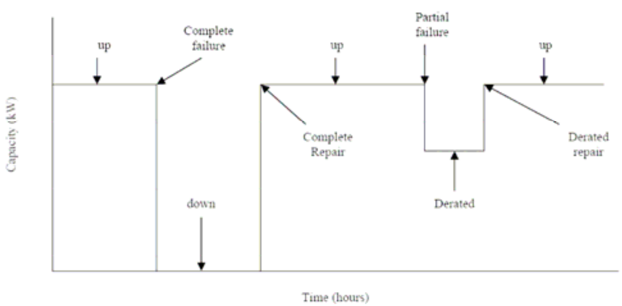

Figure 4. Illustration of outage history of a generating unit

2.3.2 System Well-being

Given the MCS outage histories of all generation units (wind and conventional), and load data, the well-being and system indices described by Billinton and associates (Billinton et al, 1996; Billinton and Karki, 1999, 2004) for the system adequacy assessment can be evaluated. The system well-being model uses three basic states to qualify the condition of the system: healthy, marginal and risk. In order to determine the operation state, all the generating units' outage histories were combined and compared to the hourly load and the accepted deterministic criterion. The load profile is an annual hourly load where the load changes discretely every hour and is constant throughout the hour.

The system state is considered healthy for hour i ('$t(H)_i$') when the system load profile is less than or equal to the available generation capacity minus the capacity of the largest generation unit. When the load profile is less than or equal to the available generation capacity but greater than the available capacity minus the largest generation unit, then the system state is marginal ('$t(M)_i$'). When the load profile is greater than the available generation capacity, then the system state is at risk ('$t(R)_i$').

The well-being indices are defined with the following equations (Billinto and Karki, 2004):

$$\text{Healthy State Probability, P (H)} = \frac{\sum_{i=1}^{n(H)} t(H)_i}{N * Yearinhours} \quad (5)$$

$$\text{Marginal State Probability} = \frac{\sum_{i=1}^{n(M)} t(M)_i}{N * Yearinhours} \quad (6)$$

$$\text{Loss of Load Probability, LOLP} = \frac{\sum_{i=1}^{n(R)} t(R)_i}{N * Yearinhours} \quad (7)$$

Where n(H), n(M), and n(R) are the number of healthy, marginal and risk states respectively, and t(H), t(M), and t(R) were recorded for entire N simulation years.

2.3.3 Wind-Conventional Operating Constraints and Indices

For the case of electrical systems with large amounts of wind generation, the rapid fluctuations in the WTG supply become the main cause of power imbalance rather than the load variations in a conventional system. A way to improve the control is to impose an operating constraint that limits the wind power to a fixed fraction of the total demand. This operating constraint forces the wind power generation to follow the load fluctuations.

The operating constraint selected was the ratio of the wind energy to conventional plant capacity energy dispatched. From the above operating constraint definition, the following indices can be defined (Billinton and Karki, 2004).

Fuel energy saving

= Total expected energy supplied by all WTGs

Let,

W_i = total available wind generating capacity

G_i = total available conventional generating capacity

L_i = load in hour *i*

N = number of sample years

x = W: G ratio

Therefore the Expected Wind Energy Supplied (EWES) can be calculated as,

$$EWES = \frac{\sum_{i=1}^{N * yearlyhours} WL_i}{N}$$

Where,

$$WL_i = L_i x \text{ for } W_i \geq L_i x \text{ and } G_i(1-x) \geq L_i \quad (9)$$

$$WL_i = W_i \text{ for } W_i < L_i x \text{ and } G_i(1-x) \geq L_i \quad (10)$$

And for load curtailment conditions,

$$WL_i = G_i x \text{ for } W_i \geq G_i x \text{ and } G_i(1-x) < L_i \quad (11)$$

$$WL_i = W_i x \text{ for } W_i < G_i x \text{ and } G_i(1-x) < L_i \quad (12)$$

Also the Expected Surplus Wind Energy (ESWE),

$$ESWE = \frac{\sum_{i=1}^{N * yearlyhours} (W_i - WL_i)}{N} \quad (13)$$

By using the values of EWES and ESWE, the Wind Utilisation Factor (WUF) can be determined using,

$$WUF = \left(\frac{EWES}{EWES + ESWE}\right) * 100\% \quad (14)$$

Another important index calculated was the capacity factor (CF). CF is WTG's actual energy output for the year divided by the energy output if the machine had operated at its rated power output for the entire year. The capacity factor depends on the combination of the capacities of the turbine and generator and the wind regime. Combining the CF and the WUF, it is possible to obtain the Wind Utilisation Efficiency (WUE), which gives a clear indication on how much benefit a given electrical system is obtaining from the usage of wind energy. The wind utilisation efficiency (WUE) is calculated using the following formula,

$$WUE = CF * WUF \tag{15}$$

By using the previous indexes and the well-being indexes, an assessment of the reliability of the electrical system can be done. Then, a sensitivity analysis is carried out by varying the number of WTGs to 1) observe changes on the indicators, and 2) draw conclusions with respect to the penetration of wind generation in the system.

3. Testing and Validation of Simulation Technique

In order to verify that the system adequacy assessment block of functions were producing appropriate results, the MCS generator was validated. Methods used by Billinton and Karki (1999) to validate the MCS procedure were implemented. The load and generation model from the IEEE-RTS (IEEE, 1979), with annual peak load of 2850 MW, and an installed capacity of 3405 MW with 32 generating units was used as the load demand for the method.

Table 1 shows a comparison of results yielded by Billinton and Karki (2004) and those resulted from the simulation technique. For both sets of simulated years, the simulation technique was relatively consistent in the production of its results (see Table 2).

Table 1. Basic Well-being indices

Evaluation Method	Simulated Results		Billinton's MCS results	
Simulation Years	734	858	734	858
Probability of Health	0.96166	0.96046	0.9867	0.9867
Probability of Margin	0.026478	0.028207	0.0123	0.0123
Probability of Risk	0.017359	0.016821	0.0010	0.0010

Table 2. Probability of health error

Well-being index	Simulated years error %	
	734	858
Probability of Health	2.53775	2.65936

Due to the fact that the random number generators used in the simulation technique and in Billinton and Karki (2004)'s method were slightly different, the MTTF and MTTR values also vary slightly. The difference in healthy state probability was minimal since it constituted a very large percentage of the overall system well-being probability. This was not the case for the marginal and at-risk probabilities. The marginal and at-risk probabilities were originally very small, with respect to Billinton and Karki (2004)'s MCS method. As a result, any percentage difference that occurred between results obtained from the simulation technique and the published results would be very large, even though they were small in absolute magnitude. Taking this into consideration for cases where the marginal and at-risk probabilities remained very small values, all indices were deemed to be acceptable.

In order to further evaluate whether or not the simulation technique was adequate, the frequency of occurrence in the system well-being states was compared to the published results of Billinton and Karki, (2004). Properties from histograms of the well-being indices from Billinton and Karki (2004) were compared to those used in Figures 5, 6 and 7. The major trends for acceptability of the simulation technique were the skewness and kurtosis of the figures produced.

The histograms for the probability of health were negatively skewed, with the kurtosis of the distribution also being similar (less than 3 since they were less outlier-prone). Besides, similarities existed in the distributions for the marginal probabilities and LOLP.

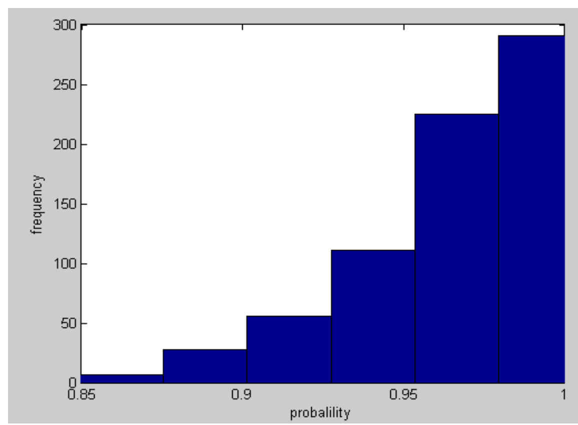

Figure 5. Healthy State Probability for the RTS

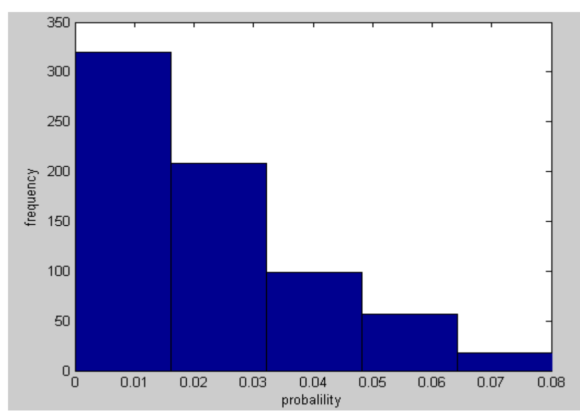

Figure 6. Marginal State Probability for the RTS

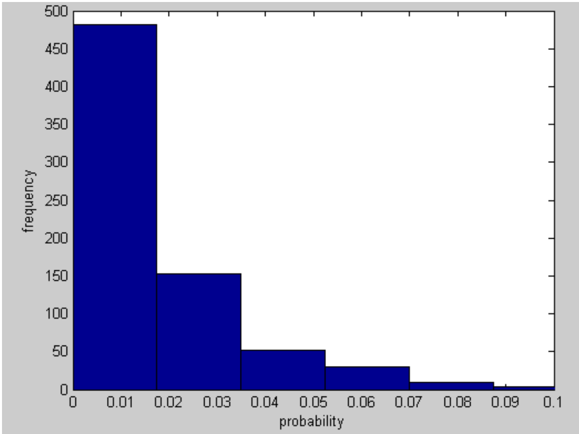

Figure 7. LOLP for the RTS

In the case of the marginal probability distribution, the histograms were positively skewed with a kurtosis similar to that of the probabilities of health. The LOLP were also positively skewed, but the kurtosis was greater since the LOLP distribution was more outlier-prone. Due to the similarities in the major characteristics of the shape and trends of the histograms, the published results (Billinton and Karki, 2004) and those produced by the simulation technique were considered to be similar.

In order to determine the consistency of the well-being results produced by the simulation technique, the MTTF and MTTR for all generating units in the IEEE-RTS generation model were reduced by a factor of 2. The FOR was maintained in order to observe the effect on the well-being indices. Table 3 demonstrates the results due to the variations.

Table 3. Effects of changes in unit failure and repair rates

	Base Case		**Doubling the failure and repair rates**	
Simulation years	734	858	356	282
Probability of health	0.96166	0.96046	0.95753	0.95342
Probability of margin	0.026478	0.028207	0.029097	0.029039
Probability of risk	0.017359	0.016821	0.018863	0.017541

5. Case Study

To illustrate the application of the method, a small electric system was assumed at a location where wind speed data was available. The wind speed data was recorded at a height of 10m with an average wind speed of 7.64 m/s. Figure 8 shows the simulated wind speed values obtained using the AR modelling methods for a leap year. The figure shows how the AR model is able to generate a wind pattern that resembles the main characteristics of the measured data, but allows for its stochastic variability. This is more noticeable in Figure 9 where the yearly seasonal trends of the observed and simulated wind conditions are compared. Similar results were observed for monthly and daily data where trends such as the sinusoidal damping which reflects the diurnal cycle, was followed by the AR model.

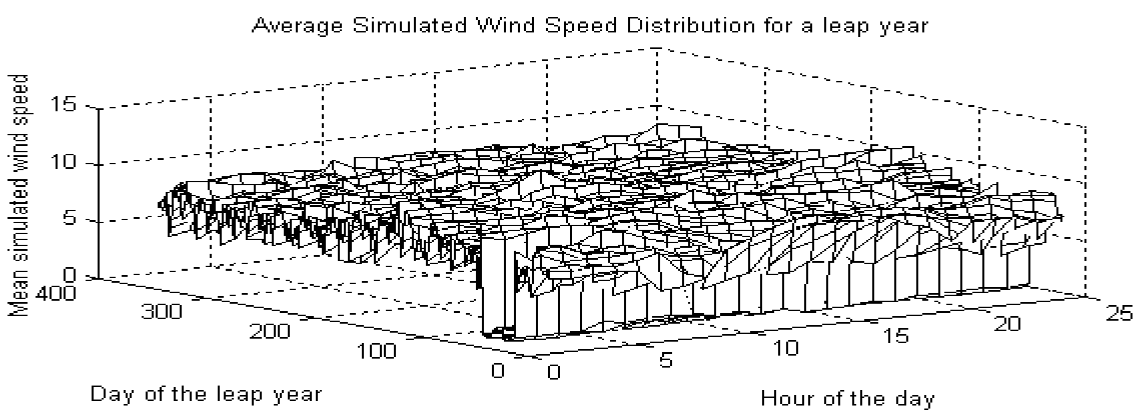

Figure 8. Mean simulated wind speed distribution

The test system represents a typical scenario of a small island or isolated system with power generation being supplied by diesel generators. The simulated electrical system consisted of 5 diesel generators with MTTF = 950h and MTTR = 50h (FOR = 0.05). The generator mix was a 20MW, a 30MW, two 50MW and a 70MW generator. The maintenance period for each type of generator was 2, 3, 4 and 5 weeks, respectively. The load demand was simulated using the IEEE-RTS load model for a system peak load of 160MW.

WTGs rated at 1.8MW were used with MTTF = 1900h and MTTR = 80h (FOR = 0.04). The residence times for the WTGs were taken from Billinton and Karki (2004)'s wind utilisation studies. The cut-in, cut-out, and rated wind speeds were valued at 3, 25 and 11 m/s, respectively. The height of the nacelle was assumed to be 60m. The W:G ratio was chosen to be 0.1.

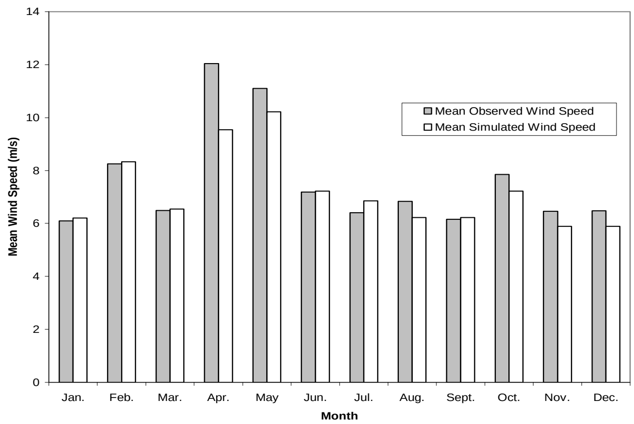

Figure 9. Histogram of the mean observed and simulated seasonal wind speeds

Figure 10 shows the system reliability and fuel offset with increasing wind capacity using 1.8 MW WTGs. As expected, the system reliability increases as the number of WTGs integrated into the system increases. The system starts with a healthy state probability of just about 0.75 for the system with only the diesel generators. The expansion of the system capacity will improve this level, and the figure shows the number of WTGs required for different levels of reliability.

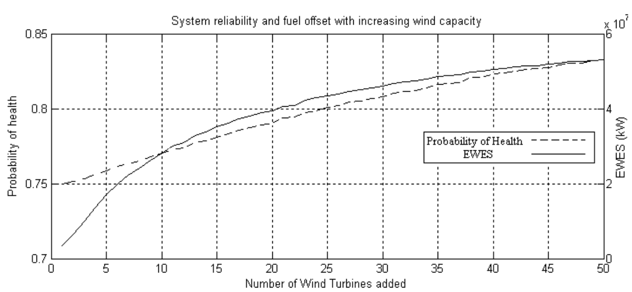

Figure 10. System probability of health and fuel offset with increasing WTGs

For example, if the desired healthy probability is 0.8, then at least 25 WTGs must be added to the system. The Expected Wind Energy Supplied (EWES) shows a tendency to level, once the number of WTG is high. This is due to the fact that the incremental amount of wind energy that can be extracted by additional WTGs decreases with increasing wind capacity installation. The value of EWES (or fuel offset) gives a clear parameter to compare and evaluate the economic feasibility of the wind generation versus the addition of conventional generation.

Figure 11 shows how the Wind Utilisation Factor (WUF) decreases as the number of WTG increases. This is dependent on the W:G ratio used for the system and gives a clear indication of how as more wind generation is added to the system the proportion that can be used by the load is reduced. This can be observed again in Figure 12, where the system shows an increasing Wind Utilisation Efficiency (WUE), until the W:G ratio boundary inhibits the contribution of the WTG. As a result, the WUF begins to drop after the WTG scheme energy contribution peak has been attained. This could be seen as indication of considering using a different W:G ratio for a higher penetration of wind generation. This will allow for a higher usage of wind as it becomes more available in the system.

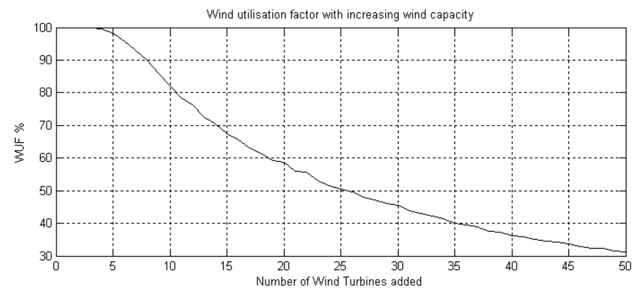

Figure 11. Wind Utilisation Factor with increasing number of WTGs

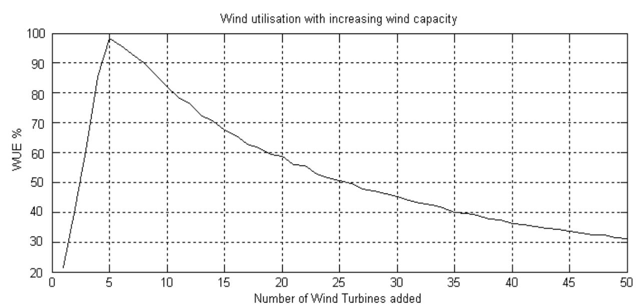

Figure 12. Wind Utilisation Efficiency with increasing number of WTGs

A slight different view of the reliability of the system is to consider the amount of wind capacity needed to maintain a constant probability of health for an increasing load demand. Figure 13 shows the number of 1.8 WTG that must be added to the generation mix in order to meet increasing load demand and maintain the reliability of the system. On this scenario, the accepted adequacy criterion was a minimum healthy state probability of 0.80. The maximum annual peak load was varied upto a value of 180 MW.

6. Conclusions

This paper has focused on the development and application of a methodology to evaluate the appropriate wind penetration in an electrical system from the reliability/generation point of view.

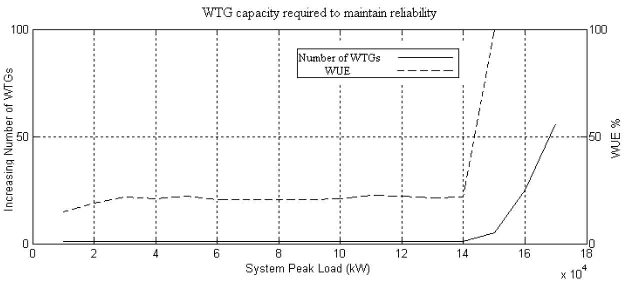

Figure 13. WTG capacity required to maintain reliability

In order to appreciate the challenge involved in assessing the impact of wind energy, the relative unpredictably of the wind itself had to be scrutinised. Winds cannot be controlled. Proposed WTG sites have to be evaluated to establish that the wind and WTG size and capacity are appropriate to meet the load demand.

The determination of the adequacy of the site hinged on the wind flows that 'fed' the WTGs. This paper presented the use of AR modelling to predict the wind speeds that would occur at any site at any time during a calendar leap year. Traditional methods of representing wind speeds were considered, but the accuracy of the AR model was considered to be appropriate to represent the system. Typical methods used by Billinton et al. (1996) were utilised to evaluate the accuracy of the simulated wind speeds.

MCS was applied in order to replicate realistic power generation variations given parameters such as MTTF and MTTR for both the WTG and conventional generating unit schemes. Given the load demand, and using the power outputs from the WTGs and conventional units in the system, the well-being probabilities were determined. Other indices (such as the WUE) were necessary to judge how much of the WTG was being utilised.

As demonstrated with the case study, the methodology allows comparison of the reliability of the system with a variable number of WTGs. Additionally; the method provides indexes that allow the economic analysis of the wind generation.

The case study of a small electrical system supplied by diesel generators proved that as long as the wind conditions are adequate, the energy yield is great enough to usefully supplement the existing conventional generating units. Besides, the evaluation indices demonstrated that such a site would prove to be effective if large number of WTGs were used with an appropriate wind to conventional energy dispatch ratio assigned.

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