Quantification of Over Speed Risk in Wind Turbine Fleets

D. McMillan and G.W. Ault, *Member, IEEE*

The effective life management of large and diverse fleets of wind turbines is a new problem facing power system utilities. More specifically, the minimization of over-speed risk is of high importance due to the related impacts of possible loss of life and economic implications of over-speed, such as a loss of containment event. Meeting the goal of risk minimization is complicated by the large range of turbine types present in a typical fleet. These turbines may have different pitch systems, over-speed detection systems and also different levels of functional redundancy, implying different levels of risk. The purpose of this work is to carry out a quantitative comparison of over-speed risk in different turbine configurations, using a Markov process to model detection of faults and repair actions. In the medium-long term, the risk associated with different assets can used as a decision making aid. For example if the operator is a utility, it may want to avoid purchasing high risk sites in the future, or may need to develop mitigation strategies for turbines at high risk of over speed.

***Index Terms*—Wind Turbine, Over speed, Risk, Markov Chain.**

I. Introduction

INCREASED numbers of wind power projects mean that in many countries power utilities have to manage a large fleet comprising hundreds of machines. The speed of technological change is such that such a fleet typically includes multiple wind turbine configurations and ratings. With such large numbers of machines comes a responsibility to understand and minimize risk. One source of operational risk which has not received much attention is the issue of over speed risk: in particular, how different configurations compare in terms of risk. In normal operation, the vast majority of wind turbines use a pitch control mechanism as the primary control method. By changing the angle of attack of the rotor blades to the wind, the control system both maximizes power conversion efficiency and provides a crucial aerodynamic braking function. Adequate operation of this braking function is necessary to avoid over-speed conditions, where the rotor spins faster than the design limits allow. In this case there is a probability that the turbine will exceed its design load limits and lose its structural integrity. This is highly undesirable because in extreme cases such an event can cause loss of life, alongside the lesser consideration of loss of an asset.

In the short term this risk is managed by maintenance targeted at the critical components. However in the medium-long term the utility has control over what sites are acquired, which sometimes involves purchase of older sites and turbines with less robust safety systems. This work shows that risk minimization objectives should also play a part in decision making.

II. Previous Work and Literature Review

The design requirements for wind turbines [1] state that "Any single failure in the sensing or non-safe-life structural parts of the systems implementing the control functions shall not lead to the malfunction of the protection functions. If two or more failures are interdependent or have a common cause, they shall be treated as a single failure." This means that the turbine should not have a single point of failure in any system needed to stop the turbine (protection function). Although there are no formal requirements on utilities for the quantification of risk associated with wind turbines, those operators with large and diverse fleets are becoming increasingly interested in better understanding and managing this risk.

The main body of work associated with this research area was carried out by researchers at ECN in the early 90's [2, 3, 4]. This represented the first time that probabilistic methods used in other safety critical environments were applied to wind turbines [2]. Among the methods suggested were fault trees, failure modes effects and criticality analysis (FMECA), reliability block diagrams and Monte Carlo simulation. State space diagrams were also suggested, however Markov Chains were not taken forward as a viable quantitative model for the analysis owing to solution complexity. However this could be remedied by using matrix multiplication instead of direct solution of the differential equations.

In [3] the authors applied these methods, looked at a structural breakdown of parts within a wind turbine and discussed failure detection methods such as inspection and condition monitoring. A fault tree analysis was carried out for the component parts such as rotor, nacelle and tower. Via this detailed analysis a flaw in the design of the studied turbine was detected and the authors suggested more sensor redundancy to cut down the risk of failure, showing the value of such an approach.

Similar analyses were presented in [4] as part of a probabilistic safety assessment. This paper highlighted the

Manuscript received November 5, 2010. D. McMillan and G.W. Ault are with the department of Electronics and Electrical Engineering, University of Strathclyde, Glasgow, UK (e-mail: dmcmillan@ eee.strath.ac.uk).

importance of a good working knowledge of the plant. State diagrams were used to categorise the wind turbine operational states. The methodology was tested successfully on two wind turbine designs.

The same authors extended their approach to deal with geographic risk [5]. Over 200 severe incidents representing 43 turbine years of operation were analysed using data from the WMEP database along with Danish and Dutch datasets. The probability of blade loss, turbine collapse etc. were quantified based on this dataset, providing a unique insight into frequency of such events. Geographic areas were classified according to 10 risk categories such as industrial area, roads etc. Maximmum blade throw distance was calculated so that areas at risk could be defined. Finally, indirect events were considered whereby a turbine failure could have secondary impacts e.g. oil tanker impact. The output of the work was a risk contour map which could be used by government to define where wind installations would be acceptable from a risk view point.

The main body of research described above has been added to by other recent work. Dorsey [6] showed that by using traditional reliability methods such as those found in [7], a comparative study of an existing pitch system and proposed design changes can be quantitatively evaluated. In this way improvements can be made at manufacture to increase the reliability of sub-systems including safety systems.

More specifically for over speed and wind turbine safety, A FMECA analysis of a wind turbine safety system was carried out successfully on a MW-class large wind turbine by Michos et al. [8].

The effective management of risk is a relatively new problem to the wind industry, however this is not the case for other power generation types. In particular, the nuclear power industry has extremely high standards of operational safety which are maintained by extensive studies into reliability and risk. A seminal introduction to these methods, which have been practiced successfully since the birth of civil nuclear power in the 1950's, can be found in [9].

III. Data Sources

Quantitative reliability data of wind turbine sub-systems can be found in [10] and have been used by various authors in reliability studies [11, 12]. However this data is not detailed enough to distinguish between different safety system configurations. Therefore a qualitative judgment must be made on reliability of safety subsystems which can then be translated into quantitative data by use of a risk assessment approach [13]. An example is shown in table I, which is an example of how organizations with an exposure to risk may establish an explicit link between qualitative and quantitative information. This approach is adopted initially in this work owing to a lack of sufficiently detailed or accessible quantitative data.

TABLE I
Risk Assessment Table

	Probability of Occurrence				
Descriptor	highly improbable	improbable	occasional	probable	Highly probable
$\lambda = 1 \times 10$ (power)	-5	-4	-3	-2	-1

TABLE II
High Level System Characteristics

Safety System Description	System 1	System 2	System 3
Wind turbine power rating	< 1MW	> 1MW	> 1MW
Active pitch actuation type	Hydraulic	Hydraulic	Electric
Pitch actuator redundancy	No	Yes	Yes
Over speed detection redundancy level	1	3	2

IV. System Characteristics

Three generic wind turbine safety systems are analysed, representing the spread of configurations available on the market. The main differences between the three generic safety systems are summarized in table II. System 1 represents a lower power rating and an older configuration where pitch control is achieved via a single actuator connected to the three blades which provide the important braking function. System 2 has hydraulic actuators for each blade and more redundancy in the over speed detection system. System 3 has an electric pitch system (motors rather than hydraulic cylinders).

Reliability block diagrams (RBDs) were constructed for each of the three safety systems, identifying the key components comprising the safety system. The models were based on inspection of operator manuals of turbines in each of the three categories, and expert knowledge of staff involved in wind turbine operation and maintenance. For brevity only system 1 is illustrated in the main text, as seen in Figure 1 (refer to appendix for systems 2 and 3).

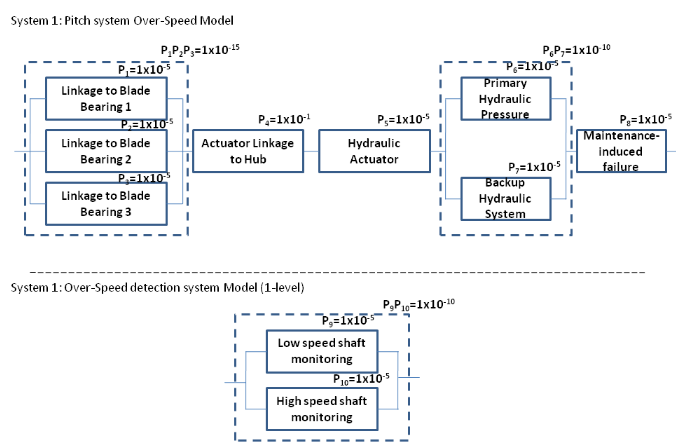


Fig. 1. Over Speed Reliability Block Diagram

The theory of reliability [14] states that for the case of series components, where failure of either component A or B indicates a possible breach in safety, the probability of failure *P(A+B)* can be computed by equation 1 (in the context of equation 1, *P(A)P(B)* is negligible and this term is dropped in equation 3). Similarly for a situation where safety critical components have functional redundancy, all components would have to fail in order to have a safety breach, and the probability of failure of both components is shown in equation 2. Taking system 1 as an example, equation 3 shows the expression for overall probability (P_{TOTAL}) of safety system failure. The procedure is repeated for systems 2 and 3 in the results which follow.

$$P(A+B) = P(A) + P(B) - P(A)P(B) \tag{1}$$

$$P(AB) = P(A)P(B) \tag{2}$$

$$P_{TOTAL} = P_1P_2P_3 + P_4 + P_5 + P_6P_7 + P_8 + P_9P_{10} \tag{3}$$

A comparison across the sub-systems is shown in Figure 2. The biggest single contributor across sub-systems is system 1 'actuator linkage to hub'. The probability of failure of this subsystem is higher than any other (this subsystem is not present in systems 2 and 3). The actuation system and over speed detection of system 2 is substantially more reliable than those of the other two systems, however it can be seen that maintenance-induced failure is more likely. Thus each system has its own strengths and weaknesses.

Figure 3 shows the overall probability of failure of the safety systems, combining all sub-systems into a single probability, P_{TOTAL}. It is observed that overall system 3 is the least likely to fail, followed by system 2. This would be intuitively expected since these represent more recent designs. System 1, representing older designs, has a substantially higher probability of failure in comparison.

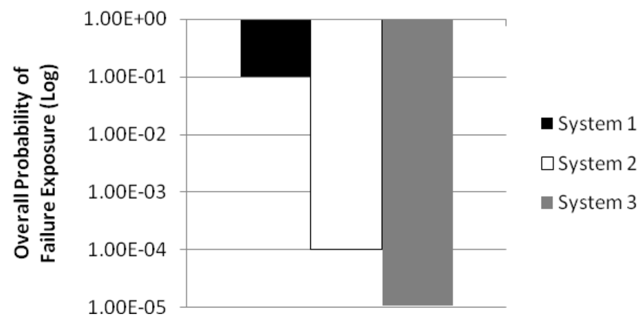


Fig. 3. Combined Probability of Failure Exposure

The reliability block diagrams for each wind turbine configuration quantify the probability of the system being exposed to failure on an annual basis. However it may be possible to detect such conditions (e.g. via bi-annual inspection) before they cause an over speed event, and perform targeted remedial actions. Alternatively, the turbine may stay in its current state of exposure for some time, or experience loss of containment event while in this more vulnerable state. To characterise this process, a Markov process has been identified as the most suitable modeling framework. Markov models have been applied in the wind domain for quantification of reliability [15] and, more recently, studies of operation and maintenance [16, 17, 18], but without much safety systems focus.

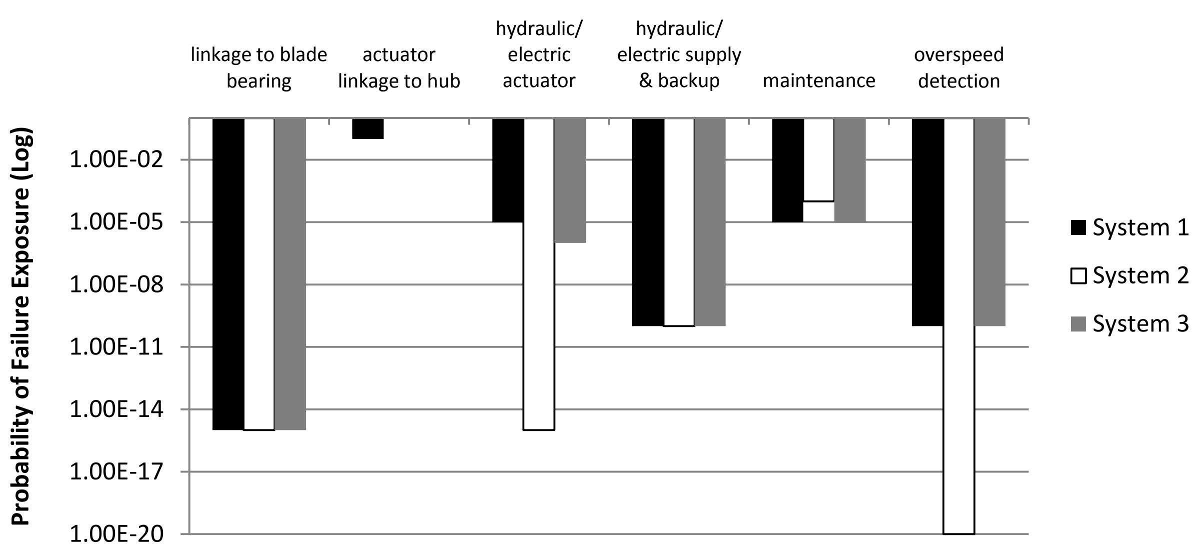


Fig. 2. Comparison of Failure Exposure Probabilities of 3 Wind Turbine Systems

V. Markov Process Definition

It is necessary to define the states which correspond to the physical condition of the plant. The transition rates (λ, μ) characterize the dynamic behavior of the system as it moves between states. These are shown in the state space diagram Figure 4. Transition rate λ_{12} corresponds to P_{TOTAL} in the RBD, that is the probability of the system being exposed to an over speed event through failure or impairment of the function of the safety system.

The safety system dynamic behavior is calculated by setting the system into differential equations. Introducing a time Δt suitably small so that the possibility of two transitions is negligible, and taking the probability of being in state one after the time step Δt:

$$P_1(t+\Delta t) = P_1(t)\lambda_{11}\Delta t + P_4(t)\mu_{41}\Delta t + P_5(t)\mu_{51}\Delta t \quad (4)$$

$$\lambda_{11}\Delta t = 1 - \lambda_{12}\Delta t \quad (5)$$

Inserting (5) into (4) and rearranging into differential equation format we get:

$$\therefore P_1(t+\Delta t) = P_1(t)\left[1-\lambda_{12}\Delta t\right] + P_4(t)\mu_{41}\Delta t + P_5(t)\mu_{51}\Delta t$$

$$\therefore P_1(t)' = \frac{P_1(t+\Delta t) - P_1(t)}{\Delta t}$$

$$= -P_1(t)\lambda_{12} + P_4(t)\mu_{41} + P_5(t)\mu_{51}$$

Similar equations can be deduced for the other states, together these are often shown in matrix form:

$$\left[P_1'(t) \quad \dots \quad P_5'(t)\right] = \begin{bmatrix} -\lambda_{12} & \lambda_{12} & & & \\ & -(\lambda_{23}+\lambda_{24}) & \lambda_{23} & \lambda_{24} & \\ & & -\lambda_{35} & & \lambda_{35} \\ \mu_{41} & & & -\mu_{41} & \\ \mu_{51} & & & & -\mu_{51} \end{bmatrix}$$

$$\times\left[P_1(t) \quad \dots \quad P_5(t)\right] \quad (6)$$

Deducing general algebraic expressions for such systems as (6) is difficult, particularly where simplifying assumptions cannot be made. In many cases in the literature, general expressions are obtained by assuming that the values of λ and μ are equal [7]. Such assumptions cannot be made for this problem, so alternative solution methods are used.

The problem can be re-formulated by discretising the Markov process. This is done by choosing an appropriate time resolution and multiplying this by the transition rate of interest. In this way we obtain (7).

$$\begin{bmatrix} 1-\lambda_{12}\Delta t & \lambda_{12}\Delta t & & & \\ & 1-(\lambda_{23}+\lambda_{24})\Delta t & \lambda_{23}\Delta t & \lambda_{24}\Delta t & \\ & & 1-\lambda_{35}\Delta t & & \lambda_{35}\Delta t \\ \mu_{41}\Delta t & & & 1-\mu_{41}\Delta t & \\ \mu_{51}\Delta t & & & & 1-\mu_{51}\Delta t \end{bmatrix} \quad (7)$$

The solution is then obtained by multiplying the matrix by itself over the period of interest. This gives the probability of residing in each state, which can be used to calculate risk.

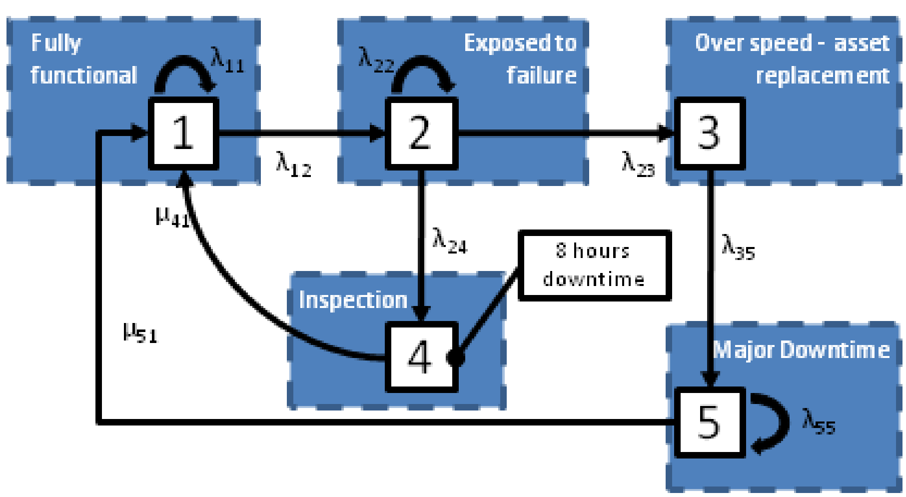


Fig. 4. Over Speed State Space Diagram

A. Markov Process Parameters

Table III summarises the Markov process parameters used in this study. The study focuses on a comparison of system 1 and system 2 over speed risk. Δt was chosen as 3 months, and so the annual rates of occurrence (λ, μ) are multiplied by 0.25 to obtain $\lambda\Delta t$, $\mu\Delta t$. The most difficult parameter to quantify is λ_{23} (rate of over speed once exposed). This is based on analysis of the dominant failure mode and its mechanism. In the case of system 1 it was determined via analysis of the system, that the probability of over speed (although greatly heightened) was relatively low even when exposed to failure (λ_{23}=0.1, $\lambda_{23}\Delta t$=0.025). On the other hand, the dominant failure mode of system 2 would almost certainly result in over speed once exposed (λ_{23}=0.9, $\lambda_{23}\Delta t$=0.225). The other main assumptions are that inspection is bi-annual (λ_{24}=2, $\lambda_{24}\Delta t$=0.5) and asset mean time to replacement is 1 year (μ_{51}=1, $\mu_{51}\Delta t$=0.25).

B. Risk Quantification Parameters

Initially the risk metrics consider only economic impacts, in terms of cost C_{TOTAL}. These arise from three sources as summarized in equation (8):

$$\mathrm{Im} = C_{TOTAL} = C_{CAP} + C_{DTIME} + C_{LAB} \tag{8}$$

Capital costs (C_{CAP}) – Asset replacement

If the system transits to state 3, this indicates a loss of containment event. Asset replacement cost is taken as £1m per MW, where system 1 wind turbine rating (WTR) is 0.5MW and system 2 is rated at 2MW. This cost is unaffected by duration of time before the unit is replaced.

Lost revenue caused by downtime (C_{DTIME}) – Asset replacement and maintenance visits

The system can suffer loss of revenue due to maintenance inspection (state 4) or asset replacement downtime (state 5). In the case of inspection it is assumed that downtime (Δ_{DT}) is equal to 8 hours. To represent this, the state probability of inspection will be multiplied by the cost of inspection (see labour costs) to determine the risk associated with inspection.

In the case of asset replacement, loss of production is taken as one annual quarter (3 months, Δ_{DT} =2016 hours). The cost to the owner, C_{DTIME}, is calculated assuming a capacity factor of 30% (CF=0.3) and electricity production credit (EPC) of £76/MWh, using equation (9).

$$C_{DTIME} = EPC\left[\Delta_{DT} \cdot CF \cdot WTR\right] \tag{9}$$

Labour costs (C_{LAB}) – Maintenance visits

Labour costs are taken as £30/hr and are worked out on the basis of a two-man team working an 8 hour shift.

In the results that follow, the risk is taken by multiplying the Cost impact (Im) for each state by each individual state probability.

VI. RESULTS

The state probabilities are obtained by populating (7) with numerical data from Table III, and then multiplying the matrix by itself for the desired time period [7]. A time period of 10 years was chosen, therefore the number of iterations was 40 for each matrix. Row 1 of the resultant matrix is of most interest as this represents each state probability given that the system started in state 1 (fully functional).

TABLE III
MARKOV PROCESS PARAMETERS

Parameter	Symbol	λ sys 1	$\lambda\Delta t$ sys1	λ sys2	$\lambda\Delta t$ sys2
Rate of exposure to over speed (P_{total} from RBD)	λ_{12}	$1\text{x}10^{-1}$	$2.5\ \text{x}10^{-2}$	$1\text{x}10^{-4}$	$2.5\ \text{x}10^{-5}$
Rate of over speed once exposed	λ_{23}	$1\text{x}10^{-1}$	$2.5\ \text{x}10^{-2}$	$9\text{x}10^{-1}$	$2.25\text{x}10^{-1}$
Rate of inspection	λ_{24}	2	$5\text{x}10^{-1}$	2	$5\text{x}10^{-1}$
Rate of transit to down state	λ_{35}	1*	1	1*	1
Repair rate if failure detected	μ_{41}	1*	1	1*	1
Replacement rate after loss of containment	μ_{51}	1	$2.5\text{x}10^{-1}$	1	$2.5\text{x}10^{-1}$

*Unity regardless of time resolution

A. State Probabilities

The steady state behavior of the system is the same regardless of starting value. The evolution of the state probabilities over each iteration are plotted in figure 5 for system 1 and figure 6 for system 2.

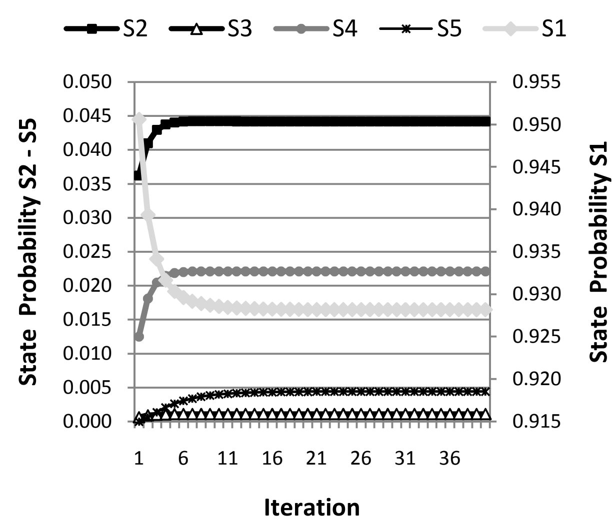


Fig. 5. Convergence of System 1

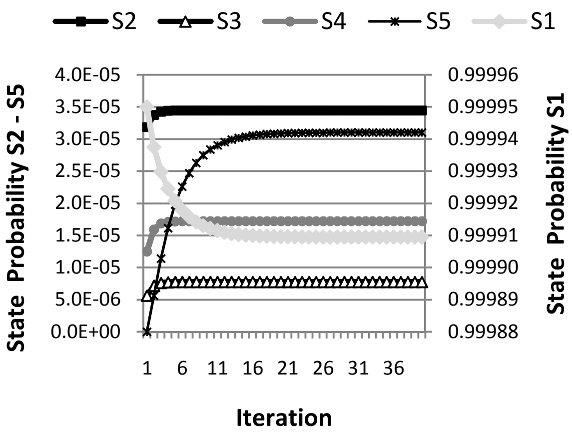


Fig. 6. Convergence of System 2

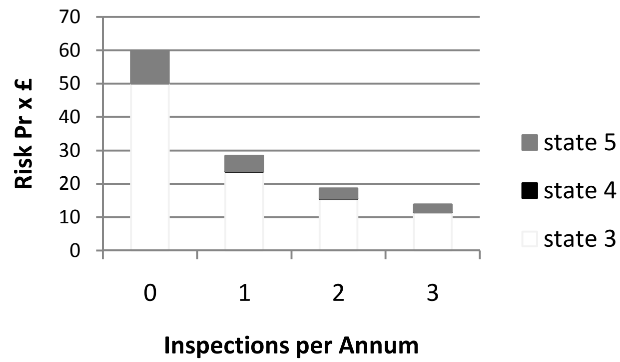


Fig. 8. Risk for System 2 States

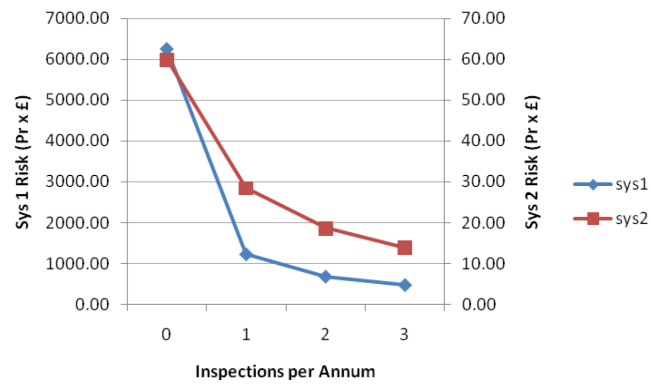


Fig. 9. Direct Comparison of System Risk

B. *Influence of Inspection Regime*

The number of inspections was varied from 0 to 3 visits per annum to establish the importance of inspection frequency on the mimimisation of over speed risk in the two wind turbine designs. Table IV summarises how the Markov process parameters change in this case.

TABLE IV
INSPECTION REGIME MARKOV PROCESS PARAMETERS

Inspections per annum	$\lambda_{24}\Delta t$	Sys 1 $\lambda_{22}\Delta t$	Sys2 $\lambda_{22}\Delta t$
0	0	0.975	0.775
1	0.25	0.725	0.525
2	0.5	0.475	0.275
3	0.75	0.225	0.025

Figure 7 shows system 1 risk contributions from each state. State 3, associated with asset replacement, dominates along with lost energy due to downtime inflicted by time spent in state 5. Figure 8 shows the result for system 2 risk. It can be seen that the risk for system 2 is roughly two orders of magnitude smaller than system 1 when they are compared directly in figure 9. This figure also shows that inspections have a higher effectiveness in system 1.

Therefore it can be concluded that inspection as a means of controlling over speed risk is much more cost effective on older, system 1 wind turbines than newer system 2 turbines.

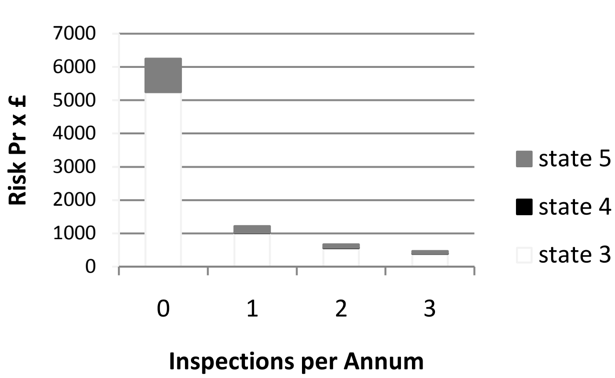


Fig. 7. Risk for System 1 States

C. *Implications for Wind Turbine Fleets*

An important issue related to individual system safety is how the probability of an over speed event (due to failure of the safety system) scales with increasing number of installed turbines. Many wind farm operators expect to grow their fleets substantially in the near to medium term if support arrangements for wind power remain in place. The question of how this up-scaling affects their risk exposure is of great interest. For this reason, figure 10 shows potential growth in the number of system 2 wind turbines installed. The risk scales linearly with the number of machines in the field.

It is interesting to note that, in terms of over speed risk, even a high number of system 2 turbines does not exceed the risk of roughly 20 system 1 turbines (typical wind farm size). In practical terms this illustrates how much safety systems in wind turbines have improved in recent years (especially in terms of functional redundancy), but also shows the importance of good training for wind turbine technicians in order to minimse risk of an over speed event, since the main contributor to system 2 turbine probability of failure is maintenance-related. This is one area where the wind farm operator has long-term control over the risk (once the warranty period has elapsed), although inevitably some turbines are easier to maintain than others.

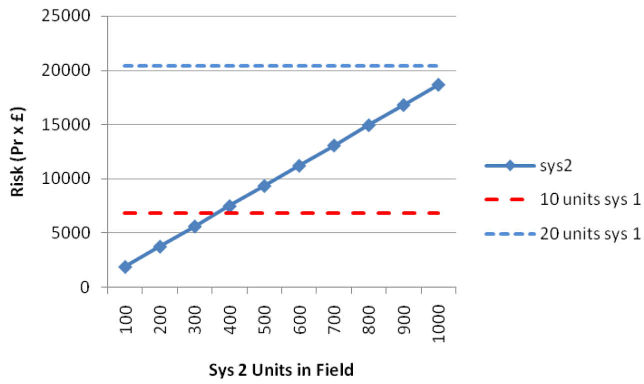


Fig. 10. System Risk in Terms of Numbers of Units in the Field and Safety System Type

There is a second main conclusion concerning acquisition policy of wind farm owners such as utilities. The higher over speed risk associated with older machines (such as system 1) should be taken into consideration when acquisitions are made, with special attention given to possible over speed issues. Without due consideration of the analysis presented here, utilities could end up taking on significant future economic liabilities they are unaware of. Such risk can be significantly reduced via more frequent inspection, as shown in this paper.

The alternatives in terms of risk reduction are, in the mid-long term, to re-power the site or to avoid acquiring older turbine designs.

VII. Conclusions

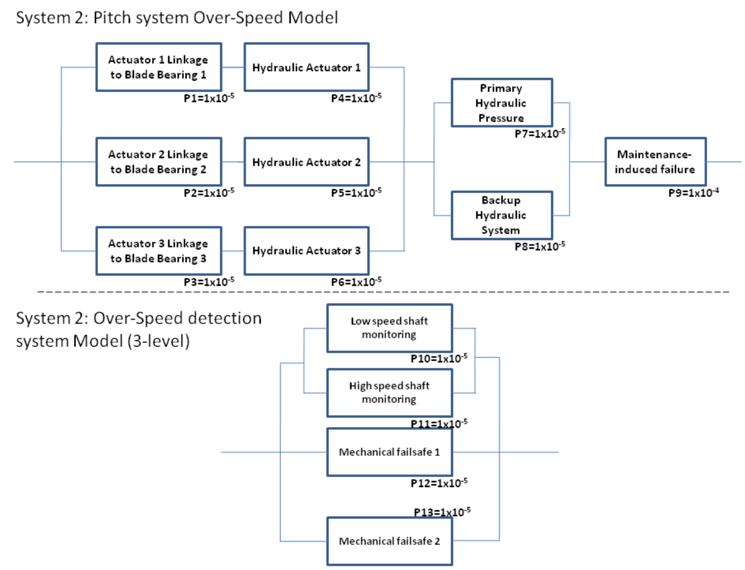
The life management of wind farms is growing in importance as more turbines are installed. Operators are likely to have fleets comprising many turbine types with different safety systems. By analysing the reliability of key subsystems such as the pitch system, and over speed detection system, operators can get a better idea about their exposure to risk. This risk is a function of the design of the safety systems of those turbines and is also proportional to the number of operational turbines in the fleet. This paper has shown that more modern safety systems represented by system 2 are much more reliable than older systems represented by system 1. This is primarily because of increased functional redundancy in modern wind turbine safety systems.

Mitigation strategies are available to control the risk of older turbine types such as system 1. It is emphasized that inspection is a useful and practical tool to reduce risk of over speed in older machines such as system 1 turbines. However there are other avenues going forward, such as increased use of condition monitoring. The existing CMS signals such as blade pitch angle can be used as a measure of pitch system health. Major failure of the pitch system in particular may be detectable by interpretation of pitch angle variation as captured in WT SCADA. No extra capital cost is required, however several extra man-hours of data processing will be needed.

Another alternative mitigation strategy is conducting detailed fault tree analysis on the safety system for greater understanding of malfunction triggers. Such analysis is highly specific to individual designs, and is the basis of ongoing work by the authors.

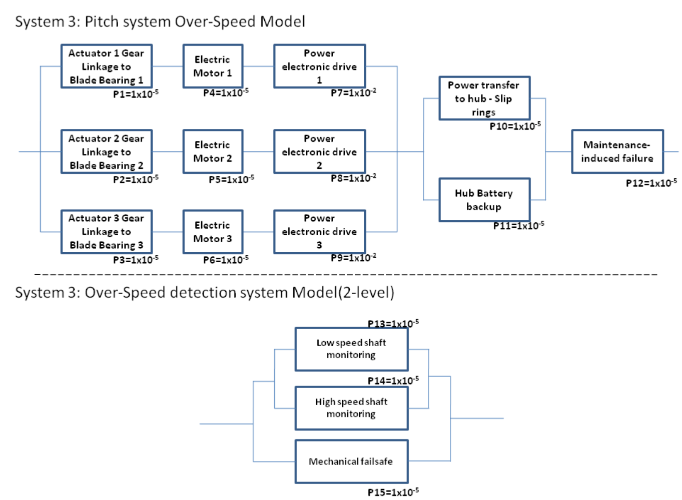
It should be highlighted that geographic risk was not included in the analysis. Such risk can be significant as shown by the authors of [5]. It would be interesting to see how geographical or environmental risk affected the conclusions in figure 10 in particular.

Appendix



System 2 is described by (10)

$$P_{TOTAL} = (P_1 + P_4)(P_2 + P_5)(P_3 + P_6) + P_7 P_8 + P_9 + P_{10} P_{11} P_{12} P_{13} \quad (10)$$



System 3 is described by (11)

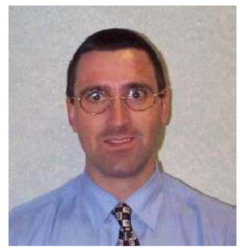
$$P_{TOTAL} = (P_1 + P_4 + P_7)(P_2 + P_5 + P_8)(P_3 + P_6 + P_9) + P_{10} P_{11} + P_{12} + P_{13} P_{14} P_{15} \quad (11)$$

REFERENCES

[1] IEC 61400-1:2005 Wind turbines. Part 1: Design requirements.
[2] Rademakers, L.W.M.M., Blok, B.M., Van den Horn, B.A., Jehee, J.N.T., Seebregts, A.J. and Van Otterloo, R.W. 'Reliability Analysis Methods for Wind Turbines' Task 1 of the project: Probabilistic Safety Assessment for Wind Turbines. June 1992, ECN-C--92-018
[3] Rademakers, L.W.M.M., Seebregts, A.J., Van den Horn, B.A., Jehee, J.N.T. and Blok, B.M. 'Methodology for Probabilistic Safety Assessment of WInd Turbines' 1993, ECN-C--93-010
[4] Rademakers, L.W.M.M, Seebregts, A.J. and Van den Horn, B.A. 'Introduction of Probabilistic Safety Assessment in Wind Turbine Engineering' AWEA WINDPOWER '93 CONFERENCE, SAN FRANCISCO, JULY 1993 ECN-RX--93-073
[5] Braam, H. and Rademakers, L.W.M.M. 'Guidelines on the Environmental Risk of Wind Turbines in the Netherlands' Global Wind Energy Conference, Paris, 2002 ECN-RX--04-013
[6] Dorsey, G. Reliability and Safety Model Alternatives for Electric Pitch Control Systems. Proc. EWEC 2009, Marseilles March 2009.
[7] Billinton, R. and Allan, R.N. Reliability Evaluation of Engineering Systems. 2nd Edition, Plenum Publishing, 1992
[8] Michos, D., Dialynas, E. and Vionis, P. Reliability and safety assessment of wind turbines control and protection systems. Wind Engineering, 2002, v 26, n 6, p 359-69.
[9] Vesley, W.E., Goldberg, F.F., Roberts, N.H. and Haasl, D.F. Fault Tree Handbook NUREG-0492, 1981, U.S. Nuclear Regulatory Commission.
[10] Windstats newsletter, URL: http://www.windstats.com/
[11] Tavner, P.J. Xiang, J. and Spinato, F. Reliability Analysis of Wind Turbines. Wind Energy, 2007, v10, n1, p 1-18.
[12] Hahn, B. Reliability Assessment of Wind Turbines in Germany, European Wind Energy Conference, 1999, Nice, France, March 1-5
[13] Modarres, M. Risk Analysis in Engineering: Techniques, Tools, and Trends. CRC Press, 2006. p6
[14] O'Connor, P.D.T., Newton, D. and Bromley, R. Practical Reliability Engineering. 4th Ed. Wiley 2002.
[15] Castro Sayas, F. and Allan, R.N. 'Generation availability assessment of wind farms', IEE Proceedings: Generation, Transmission and Distribution, v 143, n 5, p 507-518, Sep 1996
[16] McMillan, D. and Ault, G.W. 'Quantification of Condition Monitoring Benefit for Onshore Wind Turbines: Sensitivity to Operational Parameters', IET Renewable Power Generation, v 2, n 1, pp 60-72, March 2008
[17] Byon, E., Ntaimo,L., and Ding, Y. 'Optimal maintenance strategies for wind turbine systems under stochastic weather conditions' IEEE transactions on reliability vol.59 issue 2 p.393 -404 June 2010
[18] Besnard, F. and Bertling, L. 'An Approach for Condition-Based Maintenance Optimization Applied to Wind Turbine Blades' IEEE Transactions on Sustainable Energy, v 1, n 2, p 77-83, July 2010

David McMillan received the B.Eng. in Electronics and Electrical Engineering from the University of Glasgow in 2002, and the M.Sc. and Ph.D. degrees from the University of Strathclyde in 2005 and 2008 respectively.

Currently he holds the post of Research Fellow within the Institute for Energy & Environment at the University of Strathclyde. Previously he was a Manufacturing Engineer with Methode Electronics from 2002-2004, working on development of production line automation. His primary research interests are wind turbine O&M and power plant economics.



Graham W. Ault received the B.Eng. in Electrical and Mechanical Engineering and Ph.D. in Electrical Power Systems from the University of Strathclyde in 1993 and 2000 respectively. His current research portfolio at Strathclyde, where he is a Professor, spans several aspects of distributed and renewable generation, asset management, and power system planning and development. He has been actively involved in national and international initiatives to advance the development of the renewable energy industry through the IET, IEEE, CIRED and IEA.