Techno-Economic Evaluation of Condition Monitoring and its Utilisation for Operation and Maintenance of Wind Turbines using Probabilistic Simulation Modelling

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"The more you understand what is wrong with a figure, the more valuable that figure becomes"

Kelvin

"In order to succeed, we must first believe that we can."

Kazantzakis

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Abbreviations

Abbreviation	Descriptor
A	Availability
ACF	Auto-Correlation Function
ANN	Artificial Neural Network
AR	Auto-Regressive
CAPEX	Capital Expenditure
CBM	Condition Based Maintenance
CBMDM	Condition Based Maintenance Decision Model
CDF	Cumulative Distribution Function
CF	Capacity Factor
CM, CMS	Condition Monitoring, Condition Monitoring System
C_p	Coefficient of Performance
CT	Current Transformer
DAFOR	Derating Adjusted Forced Outage Rate
DFIG	Doubly-Fed Induction Generator
DGA	Dissolved Gas Analysis
E&E	Electronic and Electrical
E_k	Kinetic Energy
FOR	Forced Outage Rate
G	Generation Installed Capacity
GW, GWh	Giga Watt, Giga-Watt-Hour
HAWT	Horizontal Axis Wind Turbine
HPP	Homogeneous Poisson Process
LCCA	Life Cycle Cost Analysis
m	Mass
MA	Moving Average
MCS	Monte Carlo Simulation
MP	Market Price
MSF	Modelling System Failures
MTTF	Mean Time to Failure
MTTR	Mean Time to Repair
MW, MWh	Mega Watt, Mega-Watt-Hour
O&M	Operation and Maintenance
OPEX	Operational Expenditure
PACF	Partial Auto-Correlation Function

PD	Partial Discharge
PDF	Probability Distribution Function
PRN	Pseudo-Random Number
p	Probability
P(t)	Time-dependent Probability
PV, NPV	Present Value, Net Present Value
R	Revenue
R(t)	Reliability at time t
r	Radius
r_i	Residual of data point i
RCM, RCAM	Reliability Centred Maintenance, Reliability Centred Asset Management
RO, ROC	Renewables Obligation, Renewables Obligation Certificate
s_n	Markov State n
SCADA	Supervisory Control and Advanced Data Acquisition
TBM	Time Based Maintenance
TDM	Time Delay Model
TOC	Total Outage Consequence
TPM	Transition Probability Matrix
v	Velocity
VAWT	Vertical Axis Wind Turbine
VT	Voltage Transformer
WT, WF	Wind Turbine, Wind Farm
Y	Yield
α	Repair Cost Factor (Percentage of Component Capital Cost)
β	Component Replacement Probability
Γ	Gamma Function
γ	Auto-covariance of time series
λ	Failure Rate, Transition Rate
μ	Mean, Repair Rate
$\varnothing$, ρ	Autocorrelation Coefficient
ρ	Air Density
σ, σ^2	Variance, Standard Deviation

Abstract

Condition monitoring systems are installed in wind turbines with the goal of providing component-specific information to wind farm operators, which is the key prerequisite of a condition-based maintenance policy. Theoretically, adoption of a condition based maintenance policy will increase equipment availability, operational efficiency and economic yield: this is achieved via maintenance and operating actions based on the condition monitoring information. As with many good theoretical ideas, condition monitoring for wind turbines is imperfect. This fact has inhibited widespread utilisation of the technology and associated maintenance policies until now. Electricity generation companies' experience of such systems is mixed: the most widely-held view being that onshore wind turbine condition monitoring systems are not cost-effective (or marginally so), whereas in the offshore case, economic and technical benefits of CM systems will be substantial – closer to the theoretical case. These views, however, are based on anecdotal evidence and extrapolation rather than any kind of analytic approach, and such perceptions cannot take account of all the relevant factors. It can be concluded that the economic case for condition monitoring applied to wind turbines is currently not well quantified and the factors involved are not fully understood.

In order to make more informed decisions regarding whether deployment of condition monitoring for wind turbines is economically justified, a methodology for capturing the processes involved is proposed in this thesis. The specific form of the methodology is quantitative analysis comprising probabilistic methods: discrete-time Markov Chains, Monte Carlo methods and time series modelling. The flexibility and insight provided by this framework captures the operational nuances of this complex problem, thus enabling quantitative evaluation of wind turbine condition monitoring systems and condition based maintenance in a variety of operational scenarios. The proposed methodology therefore tackles a problem which has not been addressed in literature or by industry until now.

Acknowledgements

I would like to extend my warmest thanks to Dr. Graham Ault for his support, thoughtful guidance and positive words throughout the duration of my research. I could not have hoped for a better advisor.

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David McMillan, Glasgow, May 2008

1 Introduction

Wind power is currently regarded by many policy makers and utilities as the renewable energy source most suited to delivering desired targets on carbon emission reductions and diversity of supply. For this reason major utilities are driving forward with planning and construction of wind farms, with over 10GW wind capacity currently in the UK planning system alone (NGT, 2007). Additionally, recent UK policy documents have re-iterated government support for the wind industry in the form of the renewables obligation (RO) until at least 2027 (BERR, 2006). If these trends continue, future utilities will have generation portfolios comprising a substantial proportion of wind power.

The operational nuances of wind turbines (WT) are quite different from the existing power stations such as coal, gas and nuclear. In the first instance, the operation and maintenance (O&M) of wind turbines is coupled with weather conditions in a way which is not experienced by traditional power plants. Furthermore, instead of a single turbine hall perhaps comprising less than ten electrical generators rated in 100s of MW, a wind farm is likely to be spread over a much larger geographical area, and comprise many more generators of perhaps 1-5MW, each with its own independent sub-systems. It is clear that new challenges in terms of O&M will have to be faced, and that traditional approaches may not necessarily be effective and efficient in this new environment.

The role and benefits of condition monitoring (CM) in traditional power plant O&M has been well established for some time due to extremely high value of the monitored plant, severe cost penalties for unplanned outage of a large generator, as well as health & safety considerations. These issues certainly help to make the case for a maintenance strategy at least partially based on condition information. From a theoretical perspective, such a condition-based maintenance (CBM) system offers several benefits over scheduled maintenance. Implementation and practical difficulties, however, are sometimes a decisive factor and will also be investigated in this thesis.

Intuitively, and in contrast to large centralised plant, the individual low profit nature of discrete WT units renders the economic aspects in favour of CM less significant. Ultimately, the attitudes of wind farm operators, forever keen to operate their plant as economically as possible, can be summed up by the following statement:

"Any wind farm maintenance policy based on condition monitoring information must have clear financial benefits relative to other maintenance policies: otherwise the initial outlay for the CM system and associated costs cannot be justified, and a more traditional maintenance policy is likely to be adopted."

This idea that the value of CM needs to be demonstrated or quantified appears frequently in the literature (Rademakers et al. 2003, Giebhardt et al. 2007, Hyers et al. 2006), and is increasingly debated by those within the wind industry. Manufacturers, keen to exploit the commercial opportunity, argue the case for the CM equipment and point to the theoretical benefits of condition-based maintenance such as increased planning scope and efficient use of maintenance resources.

Operators are more pragmatic, and tend to question the technical and economic value of condition monitoring. For example, the industrial partners on this research project (the biggest wind farm operator in the UK at the time of writing) often ignore the output of their condition monitoring systems completely. Until value can be demonstrated, wind farm operators are content to apply periodic maintenance even though it may not be cost-optimal. The value of this research is that the techno-economic benefits of WT CM can be quantitatively evaluated, enabling operators to take maintenance policy decisions with more insight, but without the 'roadblock' of having to physically apply CM to find out its value.

Since this research project was initiated in 2005, a number of authors have attempted to quantify the benefits of condition-based maintenance for wind farms in economic terms (Andrawus et al. 2006, 2007, Nilsson and Bertling 2007): no literature existed on this subject until these items of research were published. However a limitation of all the proposed approaches is that they only consider case studies for specific wind farms rather than developing a generic approach which can be fed data as it is available: development and implementation of such a modelling framework is the primary goal of this thesis.

1.1 Key Research Questions

Scientific investigation of this key issue of the techno-economic benefits of condition-based maintenance for wind farms is the main motivation behind the work contained in this thesis. Within this overall remit, a number of interesting issues have been uncovered by means of literature review and engagement with the academic community as well as wind farm operators. More succinctly, the questions of interest are:

- Is condition-based maintenance for wind turbines cost-effective?
- What is the economic value of CBM for WT units relative to other maintenance?
- What is the technical benefit of CBM for WT units relative to other maintenance?
- What are the necessary conditions for cost-effective WT CM systems?
- Do offshore conditions enable economic viability of wind turbine CM systems?
- Which models and methods of analysis are suitable to quantify the appropriate metrics?

The first step of this research comprised an in-depth literature review. The purpose was to gain knowledge of the methods used to model engineering problems with similar characteristics (i.e. the final question in the above sequence). Invariably these published models were quantitative in nature, which is hardly surprising, given the background to such problems are in engineering, mathematics or physics. Another trend recognised early on was that most models were probabilistic in nature as opposed to deterministic. Again, this reflects the nature of the problem: probabilistic methods are used to account for the inevitable uncertainty which will arise when a complex problem is considered, since not all factors may be explicitly modelled. It has not been the intention of the author to discount deterministic methods altogether. Rather, it is simply because probabilistic methods more effectively meet the problem specification.

In addition to being quantitative and probabilistic, the model framework must take account of the questions it is attempting to answer. Therefore, both the technical and economic aspects of wind farm operation and maintenance must be captured. This implies the operating process of the wind farm will be modelled, enabling the questions above to be answered on a quantitative basis.

1.2 Dissemination of Research Outcomes

Throughout the course of this research an effort has been made to widely communicate the ideas and methodology proposed in this thesis. This audience has not been limited to the academic community, however a number of peer reviewed publications have been produced and these are listed below.

1.2.1 Peer Reviewed Publications

1. McMillan, D. and Ault, G.W. (2006) "Evaluation of Condition Monitoring and Operational Management for Wind Power Plant", Science, Engineering And Technology Event (SET '06), Westminster, London, March 2006 (poster) available online: http://www.prosen.org.uk/pub/set06-mcmillan.pdf

2. McMillan, D. and Ault, G.W. (2007) "Towards Quantification of Condition Monitoring Benefit for Wind Turbine Generators", Proceedings of European Wind Energy Conference (EWEC '07), Milan, May 2007 (conference paper) available online: http://www.prosen.org.uk/pub/ewec07-mcmillan.pdf

3. McMillan, D. and Ault, G.W. (2007) "Quantification of Condition Monitoring Benefit for Offshore Wind Turbines", Wind Engineering, v 31, n 4, pp 267-285, May 2007 (journal paper) available online at: http://www.prosen.org.uk/pub/windeng-mcmillan.pdf

4. McMillan, D. and Ault, G.W. (2008) "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 (journal paper)

5. McMillan, D. and Ault, G.W. (2008) "Specification of Reliability Benchmarks for Offshore Wind Farms", Proceedings of European Safety and Reliability Engineering Conference (ESREL), Valencia, September 2008 (conference paper)

1.2.2 Presentations Delivered to Project Partners

Additionally, several presentations have been made to the Prosen project partners which included a large utility – Scottish Power – and two condition monitoring manufacturers – Macom and Insensys.

1. "Policy-Based Decisions/ Operational Management & Condition Monitoring", Prosen project kick-off meeting, Ross Priory, November 2005.

2. "Quantification of Wind Turbine Condition Monitoring Benefit", ITI Energy visit, Aberdeen, May 2006

3. "Goal directed configuration & Quantification of wind turbine CM benefit", Prosen project meeting, University of Stirling, March 2006.

4. "Validation Procedure For Wind Turbine Condition Monitoring Benefit Models", Prosen project meeting, University of Canterbury, September 2006 (Talk delivered by Dr. Craig Michie).

5. "Wind Farm Condition Monitoring System Economic Performance", Prosen project meeting, University of Lancaster, April 2007.

6. "Performance Improvement Measurement for PROSEN Condition Monitoring System", Prosen project meeting, University of Essex, August 2007.

7. "Sensor Failure Data and Condition Monitoring Cost Benefit", Prosen project meeting, University of Stirling, December 2007.

Further presentations were given in January 2006 and 2007 during the University of Strathclyde "Research Presentation Day", with the audience consisting of academics and industrial guests.

1.3 Existing Key Contributions to Wind Farm Operational Issues

The work contained in this thesis builds on the existing contributions from researchers which have influenced the models produced in this thesis. The research can be broadly categorised into four thematic areas.

1. Wind farm reliability (Sayas & Allan, Billinton, Tavner)
2. Autoregressive models for wind speed characterisation (Box & Jenkins, Billinton)
3. Asset deterioration and maintenance (Anders & Endrenyi, Barrata & Marseguerra)
4. Probabilistic wind farm O&M cost quantification (van Bussel, Rademakers et al.)

The most relevant characteristics of this body of research are now briefly summarised: Table 1 illustrates the most important contributions influencing the development of the methodology presented in this thesis. It is noted that only 50% of the research in Table 1 concerns wind energy. This shows that the research area of asset management and operational issues of wind farms has only recently been deemed important enough to warrant significant research effort. It has, however, been possible to port methods from other areas such as asset degradation modelling which have yet to be applied in this domain.

Author, Key Publication Date	Principal Contribution (s)
Sayas and Allan 1996	Modelling of wind farm reliability and extreme weather states in a single state space.
Barrata and Marseguerra 2002	Use of Markov chains to model equipment deterioration, solved via Monte Carlo simulation to avoid excessive model simplification and constraints.
Anders and Endrenyi 1990	Development of deterioration and maintenance models for power systems assets based on the Markov process, to evaluate technical and economic benefits of different maintenance policies.
Box and Jenkins 1970	Time series modelling suitable for capturing wind speed characteristics. Definition of simple heuristics for model selection.
Billinton et al. 1996, 2004	Use of various time series models to quantify wind farm reliability impact on power system.
van Bussel and Rademakers 2003	Original research enabling costs of offshore wind farms to be estimated. Based on probabilistic operation and maintenance models.

Table 1: Existing Influential Research Contributions

The research by Sayas & Allan (1996) comprised binary state wind turbine reliability representation combined with wind speed state in a Markov process. This approach results in a large state space: however the authors show this is manageable from a modelling viewpoint if only binary representation of the wind turbine is required. On the other hand, if intermediate states were included for modelling the deterioration process, the method would become impractical because of the unmanageable number of states.

Billinton, a close contemporary of Allan, chose to formulate a wind farm reliability model based on Monte Carlo Simulation rather than the analytic approach of Allan. However in some studies the physical state of the wind turbines are not part of the model (Billinton and Bai, 2004). Billinton also researched time series models for wind speed representation (Billinton et al. 1996). It would be churlish to mention these models without acknowledging Box and Jenkins (1970), who were the main exponents of its development, enabling autoregressive wind speed models to be specified and estimated from data.

The Markov process is also extensively used by Anders & Endrenyi (1990) in their modelling of power system asset deterioration, failure and maintenance processes. They are interested in using multi-state systems to capture the stages of deterioration, usually employing one or two intermediate states. Their analytic approach to the problem does not lend itself well to inclusion of constraints and varied operating conditions – this is the main drawback of their approach. Such problems are overcome by the ideas of Barrata & Marseguerra (2002) who model multi-state deterioration but formulate the problem in discrete time steps and use Monte Carlo simulation to solve their models. In this way, constraints and other operational characteristics can be easily included in the model, meaning less simplification of the real system is necessary.

Finally, van Bussel and Rademakers (2003) have used probabilistic representations to model operations and maintenance of offshore wind farms. They combined reliability modelling and time series modelling of wind and wave height. Aspects of all these models have influenced this research to varying extents, but the biggest influence is the research of Baratta, Marseguerra and associates at the polytechnic university of Milan.

1.4 Thesis Outline

The thesis proceeds as follows: chapter 2 summarises the technological development of the modern wind turbine, and considers a techno-economic view of condition monitoring systems. A case study, comparing the key operational characteristics of a large wind farm and a coal-fired power station, is conducted: some intuitive conclusions are drawn about the suitability of different maintenance policies for wind farms. The three main policies available for wind turbine maintenance are outlined and detail is given on condition monitoring technology and factors affecting wind farm economics.

Chapter 3 introduces methods of modelling wind turbine component condition and operation including reliability models, Markov chains and processes and autoregressive time series models. The differences of analytic solution and Monte Carlo simulation are discussed, as are discrete and continuous-time variants. The mathematics and assumptions underpinning these models are also explored.

Chapter 4 outlines the process which was used to define various aspects of the models (e.g. number of parameters, complexity etc.) and to estimate the input parameters. Simple examples are used as a tool to aid understanding of the proposed approach, and clearly demonstrate the methodology in action.

Chapter 5 contains various applications of the methodology to onshore wind turbines. Model validation is achieved by comparing the metrics produced by the program against publicly available figures or simple calculations. The effects of varying the input parameters are examined and commented on. Chapter 6 contains similar analyses, but for offshore conditions.

Finally, chapter 7 provides discussion and conclusions from both sets of results and addresses the key research questions posed in chapter 1. Possible avenues for future research are proposed.

1.5 Chapter 1 References

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2 Wind Turbine Technology and Wind Farm Operation

2.1 Technology Development, Function & Reliability

The primary function of a modern wind turbine (WT) is to convert kinetic energy in moving air to electrical power. This is achieved by conversion of the kinetic wind energy: first into rotational torque, and finally this torque drives a generator to produce electrical energy. At the time of writing, worldwide installed capacity of wind generation totalled around 75GW (GWEC 2008), which is becoming comparable to more traditional plants such as nuclear (370GW) (World Nuclear Association 2008) and hydro (715GW) (Ren21, 2006). Many of the technological breakthroughs which have enabled wind generation to be deployed on such a large scale were achieved in the latter half of the 20^{th} century, however the wind turbine has had an extremely lengthy technological development which stretches back over 2,500 years .

Primitive windmills being designed and utilised long before the birth of Christ: the first known machines were vertical axis configurations and were used for grain grinding in the Middle East, circa 700BC. The technology is thought to have spread to other parts of Asia, with the first horizontal axis machines appearing around 1000AD. It is likely that the technical knowledge was carried to Europe via the crusaders, who probably encountered it in Persia in the first instance (Ackerman & Soder, 2000).

The earliest electricity - producing wind turbines were designed and built independently by Scottish engineer James Blyth and the more famous U.S. scientist Charles Brush (Price, 2005) in the 1880's. The slightly later work of the Dane Poul la Cour has also underpinned the development of modern wind turbines. Between 1891 and 1918, la Cour developed a test windmill and pioneered the use of wind tunnels for aerodynamic testing. As a result of this work around 120 wind turbines were deployed around rural Denmark, each rated between 20-39kW (Andersen, 2007).

Various design configurations have been tested since the experiments of these pioneers: however the Gedser wind turbine, designed by Johannes Juul, a student of la Cour, can be considered the prototype design for the vast majority of wind turbines on the market (Danish Wind Energy Association, 2008). This design came to be known as the 'Danish concept', and is the overwhelmingly dominant design for modern large-scale electricity production. This is described in the next section.

2.1.1 Danish Concept Characteristics

The Danish concept comprises a 3-bladed upwind rotor, which revolves on the horizontal axis (sometimes called horizontal axis wind turbine, HAWT). The coupling between rotor and electrical generator is indirect and is achieved via a gearbox in order to increase the rotational speed to a level which can drive a relatively small diameter, lightweight generator - for reasons outlined later. A conceptual view of the energy conversion process for such a typical modern wind turbine is outlined in Figure 1.

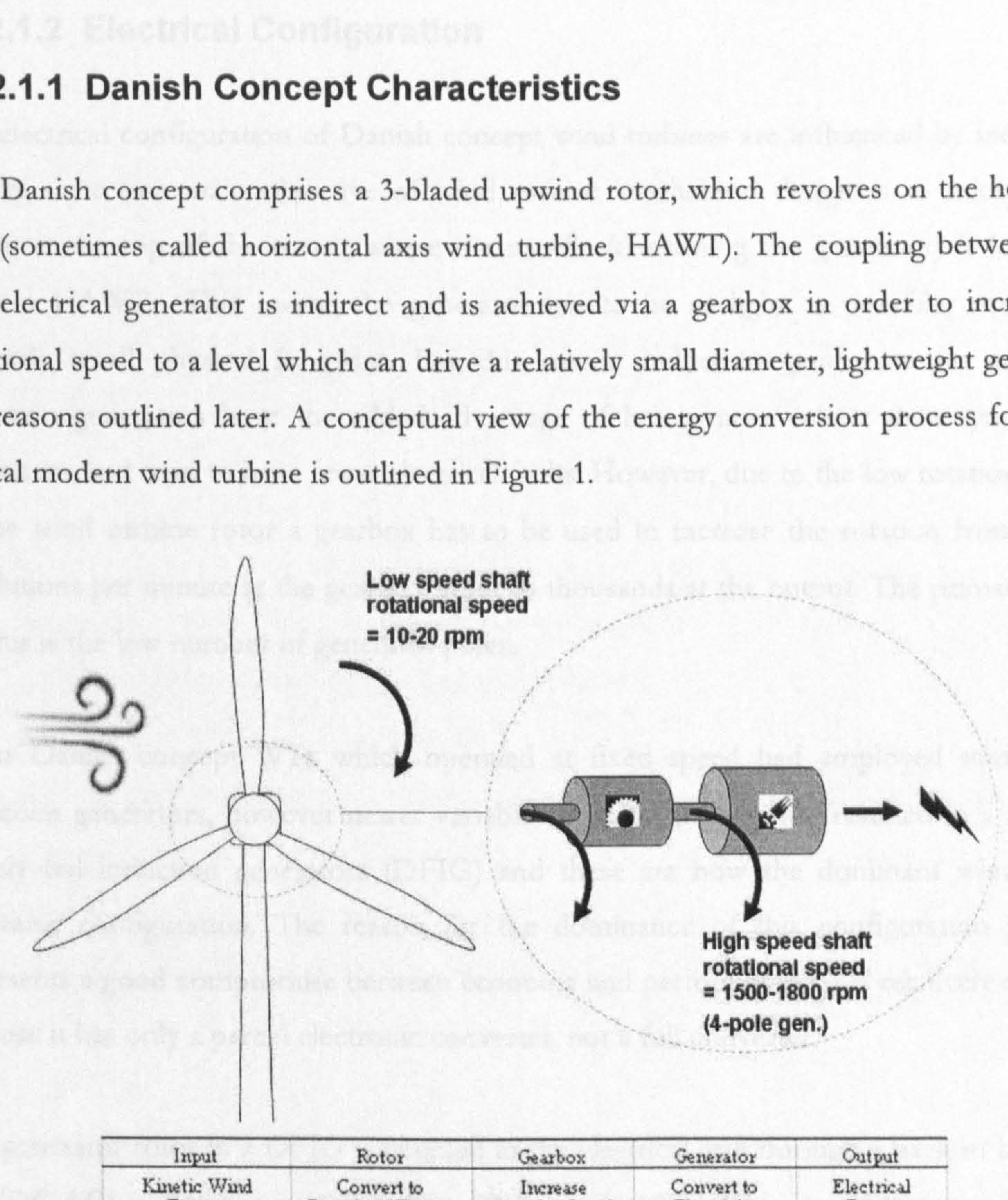

Figure 1: Conceptual Representation of Wind Turbine Energy Conversion Process

The whole wind turbine assembly rotates into the prevalent wind direction on its vertical axis by means of an electromechanical yaw system. Once facing into the wind, control of the mechanical input power is achieved either by aerodynamic design of the rotor (stall control) or by actively changing the angle of attack of the rotor blades to the wind (pitch control) via electrical motors or hydraulics.

2.1.2 Electrical Configuration

The electrical configuration of Danish concept wind turbines are influenced by mechanical aspects since one main objective of wind turbine mechanical design is to minimise the weight at the top of the tower, where the nacelle (containing the generator) is located in modern HAWTs. This means the generator has to be as light as possible, and have a relatively small physical footprint. For this reason induction generators are employed: induction generators have the added advantage of being more robust than synchronous generators, and tend to have fewer electrical faults. However, due to the low rotational speed of the wind turbine rotor a gearbox has to be used to increase the rotation from tens of revolutions per minute at the gearbox input to thousands at the output. The primary reason for this is the low number of generator poles.

Older Danish concept WTs which operated at fixed speed had employed squirrel cage induction generators, however newer variable speed technology has resulted in a switch to doubly fed induction generators (DFIG) and these are now the dominant wind turbine generator configuration. The reason for the dominance of this configuration is that it represents a good compromise between economy and performance. It is relatively economic because it has only a partial electronic converter, not a full converter.

The generator rotor in a DFIG is coupled to the electrical grid through a back to back (AC-DC/DC-AC) power converter interface (Pena et al., 1996). This configuration enables two important technical capabilities: firstly, since the rotor voltage can be controlled via the converter, the rotational speed of the machine can be varied while the generator remains in synchronism with the electrical grid. Secondly, reactive power control, which is also extremely important from the viewpoint of interaction with the electrical grid, can be achieved.

Direct drive machines utilising synchronous generators are being developed: however accommodating their larger diameter, owing to a far greater number of stator poles, is still an issue. Furthermore, the full electrical converter necessary in such a configuration may result in a much higher level of electrical faults as compared to the induction generator (Tavner, 2006a), as well as increasing the cost.

2.1.3 Reliability Metrics for Danish Concept

Since this thesis is concerned with establishing the techno-economic case for condition monitoring of WTs, a good understanding of the reliability of WTs and their components is core to exploring this topic in detail.

General measures of WT reliability are available in literature, with several studies considering only the overall number of failures per unit time, λ. In this thesis a 'failure' is defined as a shut-down of electricity production which requires a maintenance visit. This is in contrast to faults which can be corrected using a remote WT reset.

Very often λ is expressed in terms of time units of 1 year (annual failure rate). Table 2 shows how λ varies for five published studies: the data collected shows quite a large spread of values for λ. In general these values compare rather unfavourably to equivalent figures for more established plant such as gas turbines, which for which λ is roughly 0.150 (Tavner et al., 2007).

There are many possible reasons for this large spread of reliability values. Firstly, some of the values are estimates by the authors rather than data-based parameters (Sayas & Allan, 1996). Negra (2007a) and Van Bussel & Zaaijer's (2001) estimates of λ are based on expert judgement of wind farm operators. The other values are derived from recorded data sets.

Author & date	Ribrant & Bertling 2007	Ribrant & Bertling 2007	Ribrant & Bertling 2007	Tavner et al. 2007	Tavner et al. 2007	Negra et al. 2007	Van Bussel & Zaiijer 2001	Sayas & Allan. 1996
Country	Sweden	Finland	Germany	Germany	Denmark	Denmark	Holland	UK
λ annual failures	0.402	1.380	2.380	1.796	0.434	1.500	4.000	2.200

Table 2: Annual Wind Turbine Failure Rates

The studies by Ribrant & Bertling (2007) and Tavner et al. (2007) are derived from wind turbine failure statistics. The Swedish statistics are based on a population of roughly 624 WTs, but no information is given regarding the size of the other samples. The German and Danish studies by Tavner et al. (2007) comprise maximum populations of 4,500 and 2,500 respectively. Therefore, the greatest statistical significance can be placed in the value of 1.796 from the German study of Tavner: it is very interesting to note that the mean value of these 8 estimates of λ is 1.762.

A note of caution must be sounded when interpreting failure statistics such as those analysed by Tavner and colleagues. It is important to mark that the method of reporting these results may influence the Table 2 values. For example, much depends on how a failure is actually defined. Some would argue that any unplanned outage should contribute to λ. Others counter that short outages, often rectified by remote action, are insignificant. The definition of what constitutes a system failure will clearly impact on the reported figures.

Overall WT failure rates such as those summarised here are adequate for studies focusing on high level impact of failures, e.g. impact of a wind farm on the reliability of the power system. However, in this thesis operational issues are of interest. These issues encompass day-to-day electricity production, specific component failures, downtime associated with different failures, maintenance policy and monitoring capability.

It is clear that a greater level of detail must be captured for operational issues compared to high-level impact of failures. This implies the need for information on the reliability of WT sub-components.

2.1.4 Reliability at the Sub-Component Level

It has been established that the analysis of German data by Tavner et al. (2007) represents the most statistically credible estimate for overall WT failure rate among the studies considered. In their research, the authors principally investigate failure rates for WT sub-components, which is of extreme interest for a deeper understanding of wind farm operation. The sub-component data extracted from Tavner et al. (2007) is plotted in Figure 2.

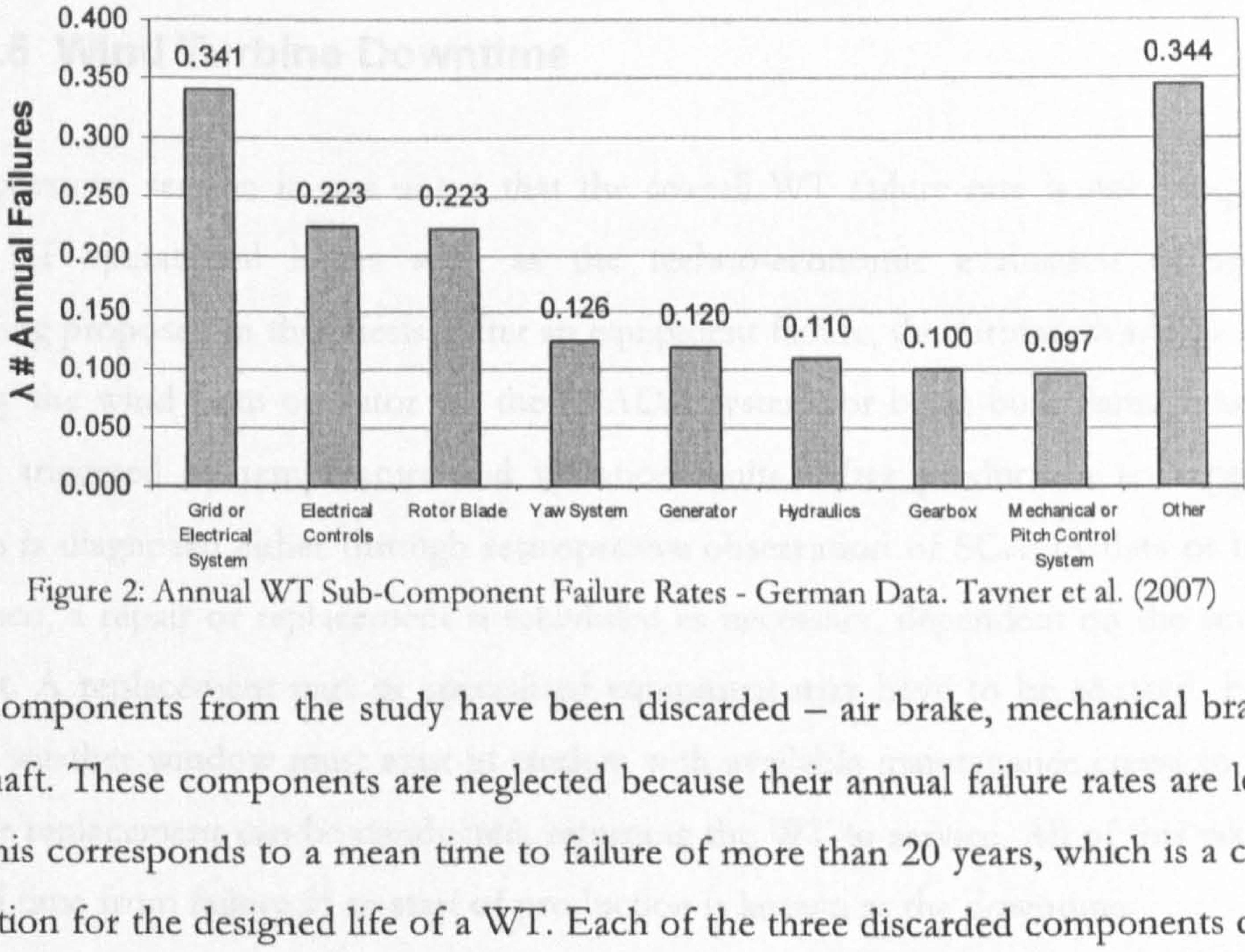

Figure 2: Annual WT Sub-Component Failure Rates - German Data. Tavner et al. (2007)

Three components from the study have been discarded – air brake, mechanical brake, and main shaft. These components are neglected because their annual failure rates are less than 0.05. This corresponds to a mean time to failure of more than 20 years, which is a common assumption for the designed life of a WT. Each of the three discarded components could be repaired or replaced if they did fail. That is to say, they do not dictate the designed life of the WT.

Inspection of Figure 2 shows that electrical–related failures (grid or electrical system + electrical controls) contribute greatly to the overall failure rate: they are responsible for 0.564 failures per annum, or around 31% of all failures. It is important to put this into context by noting that such failures can be repaired relatively easily, with very little associated downtime and loss of production as compared with outage of large mechanical components (Echavarria et al. 2007, Tavner et al. 2006a).

Furthermore, repair or replacement of an electrical or electronic sub-assembly does not require hire of heavy equipment such as a crane, since these assemblies are accessed fairly easily. It quickly becomes apparent that as well as the probability of an outage event as described in this section, the impact of the event must also be considered. This leads to the concept of risk, which is explained in section 4.3.2. This in turn implies that factors beyond the failure rate have to be considered in any thorough and realistic evaluation of wind farm operation.

2.1.5 Wind Turbine Downtime

In the previous section it was noted that the overall WT failure rate is not adequate for analysis of operational issues such as the techno-economic evaluation of condition monitoring proposed in this thesis. After an equipment failure, the turbine would be stopped either by the wind farm operator via the SCADA system, or by in-built damage limitation controls triggered by temperature and vibration limits. After production is stopped, the problem is diagnosed either through retrospective observation of SCADA data or by a site visit. Then, a repair or replacement is scheduled as necessary, dependent on the severity of the fault. A replacement part or specialised equipment may have to be sourced. Finally, a suitable weather window must exist in tandem with available maintenance crews so that the repair or replacement can be conducted, returning the WT to service. All of this takes time: the total time from failure to re-start of production is known as the downtime.

As with the failure rate, the downtime associated with individual component outages (rather than averaged downtime for all failures) should be considered, as specific failures have unique operational impacts. Downtime durations are less well documented in the literature than failure rates, possibly owing to their even greater commercial sensitivity. Nevertheless, some literature does exist, and along with expert opinion from wind farm operators, these quantities can be adequately estimated. Figure 3 is an example of such data captured by Ribrant & Bertling (2007) for Swedish failures over 2000-2004.

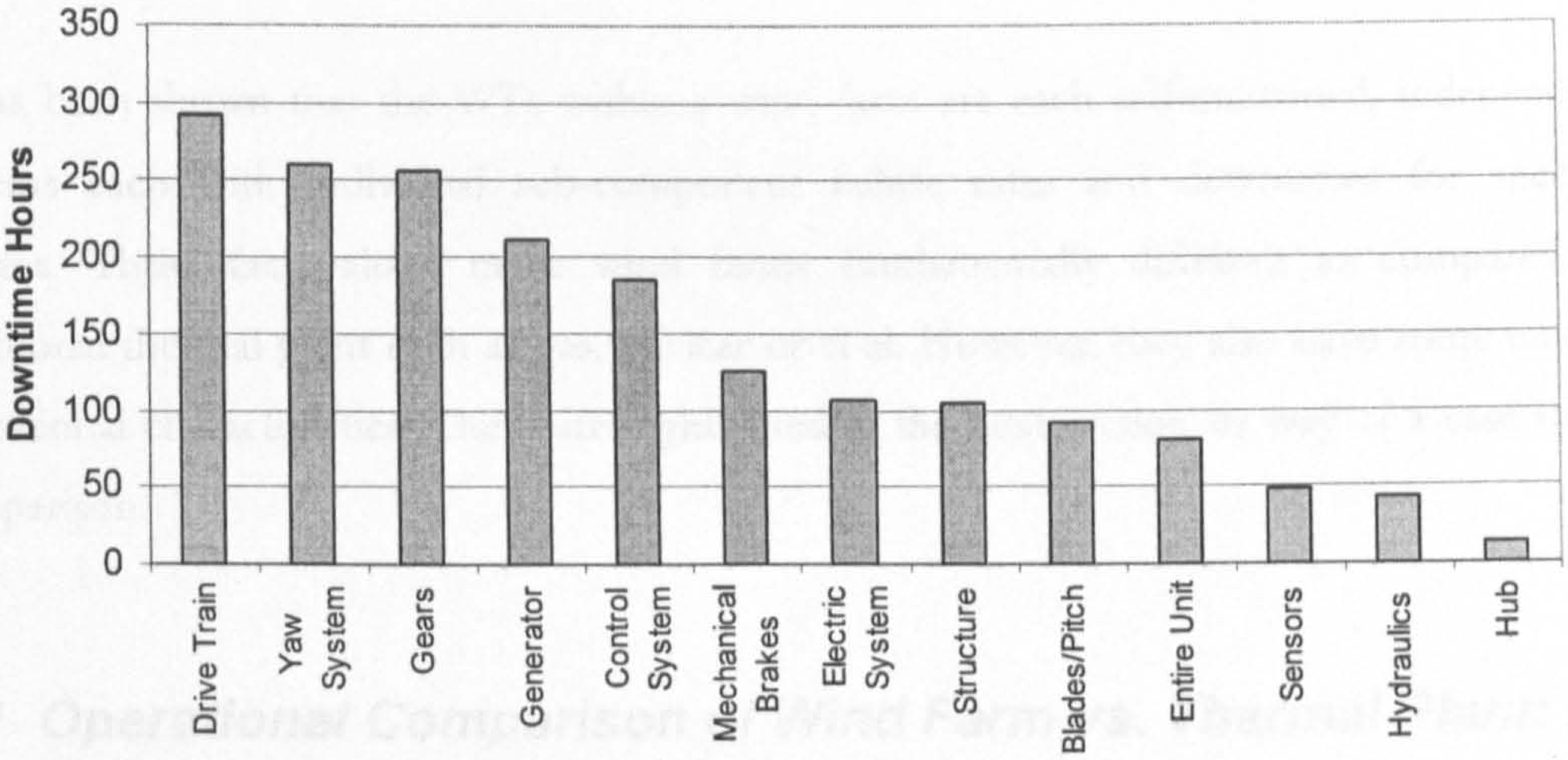

Figure 3: WT Component Downtimes. Ribrant & Bertling (2007)

Since downtime is affected by a great many factors, it is inevitable that estimates vary substantially. As an example, it has been possible during this research to get estimates of gearbox downtime (in the case of a replacement) from a number of sources. In some cases, specific conditions were attached to the downtime: these are summarised in Table 3.

Source	Ribrant & Bertling. 2007.	Operator 1. 2007.	Operator 2. 2007.	Operator 2. 2007.	Operator 2. 2007.
Conditions	Wear-related failure	Good access to site, no spare	Spare available	No spare	No spare, offshore weather constraints
Downtime Hours	601	700	168*	720*	1440*
Downtime Days	25	29	7*	30*	60*

Table 3: Gearbox Replacement Downtimes. * Denotes an estimate based on experience of Scottish Power.

The length of time required to source a major component is clearly a major factor in downtime duration. In part this may be due to undersupply of wind turbine components, a recent problem which has affected not only component lead times but that has also driven up component costs (Garrad, 2007).

Such significant periods of downtime do suggest that there is scope for optimisation of wind farm operation via effective maintenance task scheduling. In particular, weather windows for maintenance actions (usually measured in days) may be a major constraint, and their impact should be carefully considered. This is discussed in more detail in forthcoming sections dealing specifically with maintenance.

It has been shown that the WTs within a wind farm are each self-contained, independent systems each with individual sub-component failure rates and downtimes for specific failures. These facts alone make wind farms fundamentally different as compared to traditional thermal plant such as gas, nuclear or coal. However, they also have some unique operational characteristics. These are highlighted in the next section by way of a case study comparison.

2.2 Operational Comparison of Wind Farm vs. Thermal Plant: A Comparative Case Study

As has been mentioned, the characteristics of a wind farm are quite different from the traditional thermal plant equivalent. To illuminate this point further, a comparison of some key operational characteristics of two representative projects is given: both projects are currently being planned in the UK. The wind farm is Greater Gabbard, a 500MW offshore wind farm which will be built off the coast of Suffolk. The thermal plant is Tilbury power station, a 1,000MW coal-fuelled plant which will replace a similar existing coal-fired power station near the Thames estuary: their characteristics are summarised in Table 4.

The characteristics and costs were derived from (Tilbury: Npower 2008) and (Greater Gabbard: Airtricity 2008). Clearly there are a number of fundamental differences between these two plant types. These can be broadly categorised as economic, technical and logistical differences.

Name	Type	Rating MW	Capacity Factor %	Generating Units # X MW	Unit Cost £M	Geo-graphical Area Km^2	Access Distance Km	Maintenance Equipment
Tilbury	Coal-fired	1000	90*	5 X 200*	~200	<1*	0	Heavy-duty crane
Greater Gabbard	Offshore wind farm	500	40*	139 X 3.6	~3.6	147	23	Offshore jack-up crane vessel

Table 4: Comparison of Coal and Wind Operational Characteristics. Fields marked * are assumed.

2.2.1 Comparison of Unit Cost

Cost of an individual 'unit' in the two cases is very different: £200M in the case of coal-fired and £3.6M in the case of the wind turbine – nearly a factor of 10. More expensive units will obviously be treated with more care due to the huge amount of capital invested by the generation company: this is why condition monitoring is often deployed in large thermal units. The case for CM applied to the wind farm is intuitively less persuasive due to the much lower value of the individual units.

2.2.2 Comparison of Maintenance & Logistical Issues

When an outage does occur, the combination of offshore logistics (the need to travel across 23km of sea to inspect damage), offshore weather constraints and the need for a highly specialised repair vessel (with associated long lead times and costing thousands of pounds per day for hire) makes repair and replacement costs much higher than land-based systems. Additionally, traditional maintenance inspections become much less trivial for large offshore wind farms: in the case of Greater Gabbard there are 139 units spread over an area of 147km^2. Conducting a manual inspection would be both time-consuming and tedious, especially compared to the coal-fired station where the turbine hall would contain all the generation equipment, and the entire site would cover only 1 or 2 km^2. This suggests there is scope for scope for cost reduction via CM by reducing the number of unnecessary inspections.

2.2.3 Comparison of Lost Revenue

One of the main drivers of responsive O&M is to minimise any downtime that occurs after an equipment outage. This can be achieved by predicting failures through a CMS or by holding spares and having repair teams ready at short notice. In the case of a coal plant or wind farm, potential revenue will be lost: the amount of this lost revenue depends on several variables. One of these variables is the capacity factor (*CF*).

The capacity factor is a measure of actual electricity production in terms of full load hours (FLH_{actual}) relative to theoretical production (i.e. if the generator ran at full output over the considered time period - FLH_{max}). The CF is defined in equation 1: Typically the CF for a thermal plant is much higher than for an offshore wind farm, as Table 4 suggests. This is a fundamental difference between the two types of power plant.

$$CF = \frac{FLH_{actual}}{FLH_{\max}}\% \tag{1}$$

An estimate of the lost revenue, R_{lost}, for the coal-fired unit and the wind turbine can be calculated by using the CF alongside other variables. These are the length of downtime (T_{down}), electricity and renewables market price (MP_{elec}, MP_{roc} – discussed later) and rating of the generator (G). Equation 2 characterises the lost revenue for both power plants by calculating the lost energy in MWh ($CF \times G \times T_{down}$) and multiplying by the economic value of each MWh ($MP_{elec} + MP_{roc}$).

$$R_{lost} = CF \times G \times T_{down}\left(MP_{elec} + MP_{roc}\right) \tag{2}$$

Table 4 values can be substituted into equation 2, assuming market prices of £36/ MWh and £60/ MWh for MP_{elec} and MP_{roc} respectively. The plot in Figure 4 shows the lost revenue for increasing values of downtime.

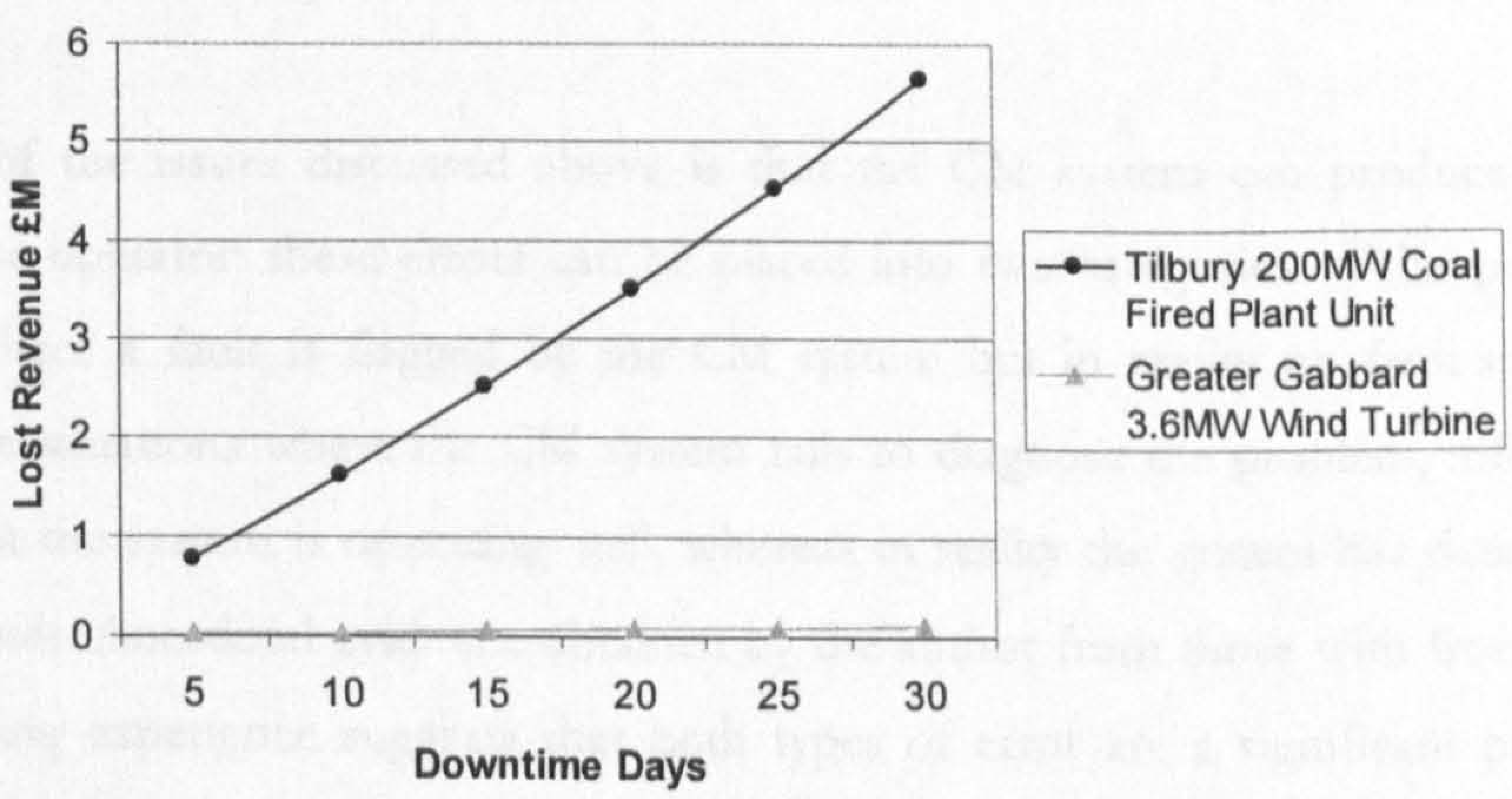

Figure 4: Lost Revenue Comparison of Coal Plant Unit and Wind Turbine

A large difference in the lost revenue for the two cases can be observed in Figure 4. This implies that minimisation of downtime is a much more critical issue for coal-fired plant as compared to an offshore wind farm, although it should be noted that multiple WT outages may close this gap. Figure 4 illustrates in very clear terms exactly why coal plant operators are keen to use tools such as condition monitoring to avoid lengthy outages. The case seems intuitively less clear for wind farm operators.

2.2.4 Implications of Condition Monitoring False Positives & False Negatives

CM systems for coal plant are very well established, having been refined over many years. The techniques are primarily based on vibration analysis and temperature trending. WT CM is based on similar technology, but problems have been encountered in using similar tools and techniques but applied to plant with very different characteristics. An example of this is the dynamic loading on the rotor and resulting variable speed operation of the gearbox and generator (Rademakers et al. 2004, Becker & Poste 2006 and Hyers et al. 2006). This is fundamentally different to how thermal plants are loaded – these technical issues are discussed later in the thesis. Other problems are transducer unreliability (especially in extreme temperatures or high humidity) and intermittent CM errors in extreme weather conditions. These two problems are direct consequences of the distributed, physically exposed nature of wind farms and are in stark contrast to the relatively controlled environment of a thermal power station.

The result of the issues discussed above is that the CM system can produce erroneous signals to the operator: these errors can be placed into two categories. False positives are situations where a fault is flagged by the CM system but in reality no fault exists. False negatives are situations where the CM system fails to diagnose the problem, informing the operator that the system is operating well, whereas in reality the system has deteriorated or suffered a fault. Anecdotal evidence obtained by the author from those with front line wind farm operating experience suggests that both types of error are a significant problem for current WT CM systems. For example, it has been said that the CM system at Horns Rev has caused more downtime than it has saved, due to false positives. This represents an extreme but possible case where a conservative operational approach is adopted, based solely on CM information. It would involve shutting down production until an inspection could be scheduled, if a fault or incipient fault is flagged by the CM system. In the case of a false positive this causes unnecessary downtime, which is exacerbated by the logistical and access issues previously discussed.

It can be derived from anecdotal evidence and literature that CM systems for wind farms may be less reliable than their thermal plant equivalent (see Becker & Poste 2006 and Hyers et al. 2006). Much research effort is currently being devoted to this topic. However this is a current problem which is highly relevant for wind farms in operation today. Therefore, the models developed in this thesis include the possibility of a fallible CM system and evaluate the impact of this factor on the techno-economic benefits of WT CM.

2.2.5 Summary of Wind Farm – Coal Station Comparison

In summary, there are conflicting themes which emerge from the presented comparison. There seems to be little economic justification for wind farm CM on the basis that the lost revenue due to outages is small compared to coal plant (see Figure 4) – although multiple WT outages will increase the lost revenue. Also the capital value of a WT is relatively small compared with a coal unit. In the offshore case the distance to shore, weather constraints and access issues make the issue of CM false diagnosis more pertinent.

Conversely, if the technical hurdles of CM are overcome (or can be adequately controlled), this represents a desirable solution to maintenance management, eliminating the need for tedious and un-necessary periodic inspection of hundreds of assets, possibly spaced over hundreds of km^2. The very fact that maintenance actions are coupled strongly with weather conditions implies the need for increased planning of maintenance activity, which can theoretically be provided by CM. Additionally, highly specialised and costly crane vessels are required for major maintenance offshore. It is observed that deciding on a maintenance policy for a wind farm is not a trivial task due to the many factors involved. The next section details the possible approaches to wind farm maintenance.

2.3 Wind Farm Maintenance Policy

Power systems assets are typically operated according to one of three maintenance policies. Wind farms, although exhibiting markedly different characteristics to thermal plant, are maintained using the same methods. These are (pseudonyms in parentheses): run to failure (reactive), periodic (time-based, preventive) and condition-based (predictive) maintenance.

2.3.1 Run to Failure

In this case equipment is maintained only after it has ceased to function. The primary reason for adoption of this strategy would be because the plant is seen as non-critical, i.e. the consequences of an outage are not severe. The other clear reason is economic constraints: however run to failure maintenance may only be economic for systems with very high reliability, or where the consequences of an outage are small.

Other possible reasons for the adoption of run to failure as a maintenance policy are physical constraints such as weather, and restrictions on access to the asset i.e. situations where it is impractical for maintenance to be conducted on a routine basis. For power systems assets, run to failure is not used for any but the least significant assets (Schneider et al. 2006). However, it could be argued that wind turbines conform to the characteristics which may enable run to failure: geographical remoteness, comparatively low economic yield of individual units and low technical consequences of outage.

Nevertheless, dialogue with major wind farm operators in the UK indicates run to failure is not adopted for wind turbines. The main motivation behind this is the desire to keep in line with manufacturers recommendations regarding maintenance. Very often a service agreement for the first few years of operation is signed with the manufacturer. This means the manufacturer is responsible for maintenance rather than the owner/ operator. Another possible reason is the lack of operator experience, with wind being a relatively new plant type. Since run to failure is generally not adopted for wind farm operation, it will not be considered in this thesis.

2.3.2 Periodic Maintenance

Periodic maintenance is the most widely adopted maintenance paradigm in any industry (Schneider et al. 2006). The premise of periodic maintenance is that maintenance actions are carried out at pre-determined intervals, e.g. every 6 months. The primary reasons for its popularity are ease of implementation, its position as the 'encumbent' maintenance policy, and the endorsement of manufacturers, whose maintenance recommendations are often followed rather rigidly by operators of the equipment. Power system utilities in particular tend to be conservative in operation of assets, fearing (perhaps rightly) that a switch to unfamiliar maintenance systems would have a negative impact on operation. The main problem with periodic maintenance is that it will never be cost- or resource-optimal because of the lack of consideration of the actual condition or need of the equipment i.e. does the equipment *require* to be maintained at a specific time? If it does not, the maintenance effort and associated cost are wasted. Equally, if a problem occurs between inspection periods, there may be no knowledge of this, resulting in a higher probability of failure once the equipment has deteriorated significantly.

2.3.3 Condition Based Maintenance

The premise of condition based maintenance (CBM) is that maintenance actions are initiated pre-emptively according to equipment condition, since the equipment is monitored with regularity as compared to periodic maintenance (in the case of on-line monitoring, this is done on a continuous basis). Access to the plant condition information means that, in theory, maintenance actions can be scheduled in an optimal manner in terms of cost, resources and efficiency of effort.

However, even in the theoretical case there are drawbacks, such as the initial investment in monitoring tools. In particular, a supervisory control and data acquisition (SCADA) system is required to relay the condition information to a control centre. Additionally, transducers are required to carry out the measurements. Furthermore, ongoing costs are incurred. Experts and/or data interpretation systems are needed to extract meaningful signals from the condition data. Although some form of human input is needed for maintenance planning for all types of maintenance policy, CM systems in particular require continual attention because a fault could develop at any continuous point in time.

These costs (SCADA, transducers and data interpretation system) are easily justifiable for a single large rotating plant rated at hundreds of MW, however the case for CM applied to wind turbines is intuitively less clear. This is because separate CM equipment is required for each turbine, even though WT ratings are relatively modest (in the range 0.5-5MW) compared to steam turbines (100's of MW)

The attitudes of wind farm operators in particular reveal several problems associated with CM. A group of these problems are simply a function of how CM is *perceived* in some industrial circles, with the main hurdle being the view that CM is ineffective and uneconomic. Another group of problems stem from *real* experience and difficulties with implementation of CM systems. Both of these groups are the focus of the next section.

2.3.4 Specific Problems with Condition Based Maintenance Applied to Wind Turbines

Anecdotal evidence suggests that CM systems are becoming more commonplace, especially installation at manufacture of larger MW-class turbines. Nevertheless, there is also a widespread perception that operational savings due to the theoretical benefits of the CM system (More operational information, increased scope for O&M scheduling and thus higher availability) are effectively neutralized by the drawbacks, which can be summed up by the following commonly-cited problems:

1. The benefit or value of CM systems for wind turbines is unclear as it cannot be easily and accurately quantified. This applies in particular to onshore wind which is considered low-margin plant by operators. It is therefore difficult to establish an economic argument.

2. CM systems for WTs are too costly to implement and drain resources in terms of:
    - Hardware/ Software
    - Man-hours required for data mining and interpretation
    - False positives and negatives, leading to un-necessary shutdowns

3. In the context of a medium or large wind farm with tens or hundreds of turbines, the loss of a single (or even a few) machine(s) is not significant from a technical, economic or indeed any other significant viewpoint.

In fact these arguments lead major utilities to simply switch off or ignore the output from their WT CM systems, and employ periodic maintenance. From an alternative viewpoint, the following could be stated in response to the points above.

Point 1: It would be useful to quantify the benefit of WT CM systems and establish what conditions need to exist for such a system to be economically justified. Indeed this has been identified in other literature (Rademakers et al. 2003, Giebhardt et al. 2007) as a research 'white spot'.

Point 2: Development of robust hardware and effective software algorithms is an ongoing issue (and, indeed, an important research area – see Hyers et al., 2006, Wilkinson et al., 2007 and Zaher and McArthur., 2007), which will become less significant as the respective designs/ architectures go through successive iterations. Well designed and robust software will filter information adequately and ensure that the operator is not overwhelmed with information and alarms. Introducing more autonomy to trending and data interpretation may also cut down on resources needed to implement the CM system.

With respect to hardware, the level of installed CM hardware should be reflective of the importance of the monitored components, as well as their reliability and ease of repair/ replacement. For example, a gearbox worth ~£100,000 merits instrumentation as compared to a power electronics subassembly of ~5,000 - 10,000. As well as the relative value, access to replace a gearbox involves significant difficulty due to its physical position at the top of the tower and its large weight – so the value of good maintenance decision making is clear.

Point 3: Several factors combine to increase the significance of outage of individual (or small numbers of) WTs. Firstly and most generally, is the cost pressure on generators as a result of the highly competitive liberalized UK electricity market. This is especially significant in countries which provide support to renewable electricity generators in the form of a feed-in tariff (or the renewables obligation system in the UK): in such cases increased revenues are available for wind farms. Additionally, many countries are considering increased subsidy mechanisms for offshore wind, which combined with higher yields and bigger offshore turbines, will increase revenue significantly. Futhermore, multiple WT outages within a wind farm may result in significant cumulative lost revenues. One final interesting motivation for WT CM is the particular case of Germany, where the use of CM systems has been encouraged by the insurance industry. WTs normally require an overhaul after 40,000 hours of operation: however this can be circumvented via installation of CM systems (Becker & Poste, 2006).

Despite the drawbacks which have been mentioned in this section, many still consider WT CM worthwhile – not least WT manufacturers. The next section provides a deeper examination of wind turbine CM and techno-economic issues surrounding its deployment.

2.4 Technical Overview of Condition Monitoring Systems for Wind Turbines

A comprehensive table of possible monitoring solutions has been compiled through review of publications, industry literature and consultation with wind farm operators. This is displayed in Table 5, along with the physical position of the components in Figure 5.

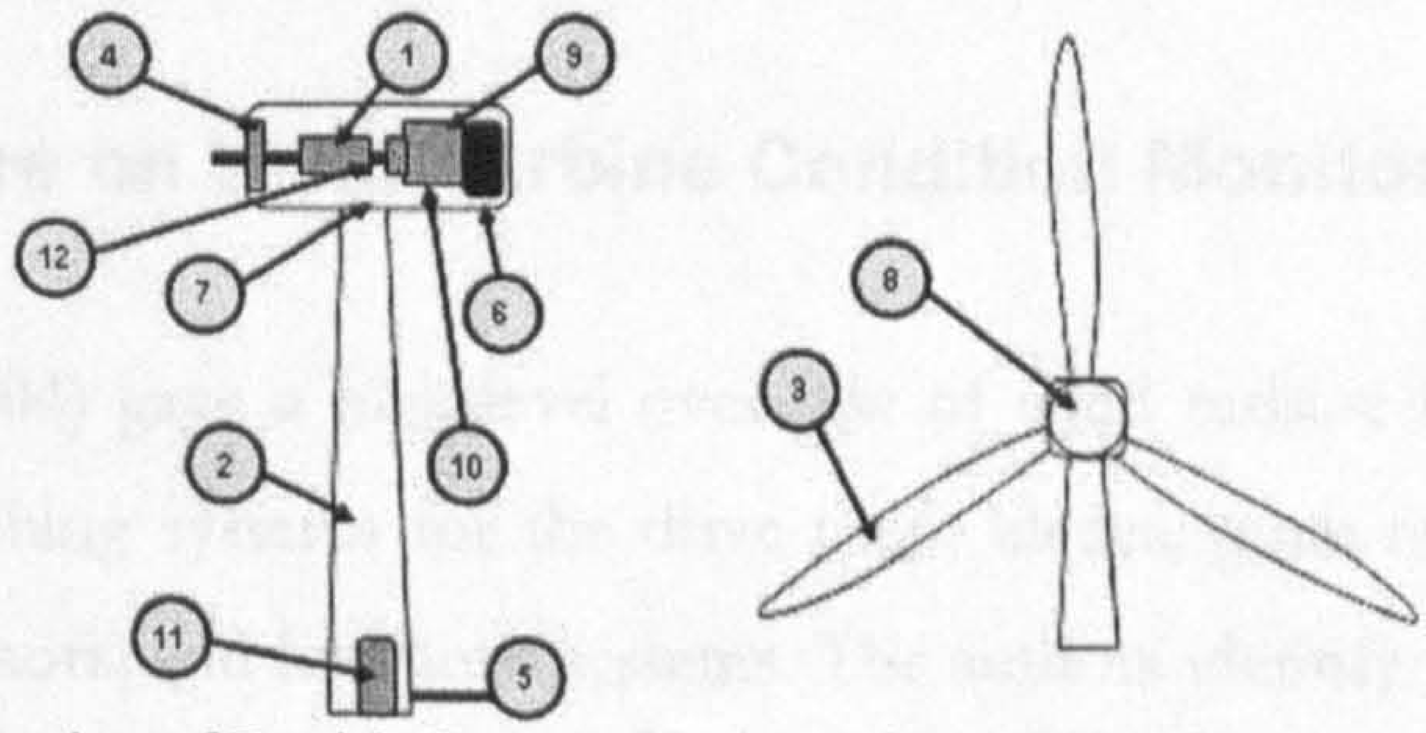

Figure 5: Location of Danish Concept Horizontal Axis Wind Turbine Components

FIG #	WT Component	Type of Measurement	Possible Sensor Type(s)	Associated Failure Mode(s)
1	Gearbox	Vibration, Temperature, On-line oil analysis	Accelerometer, temperature sensing, hall effect sensor	Loss of energy conversion efficiency, contamination of lubricant, gear tooth damage
2	Main Tower	Vibration	Accelerometer	Structural fatigue/ failure
3	Blades	Vibration, strain, crack detection, tip speed	Optical, Strain gauge, Ultrasonic, accelerometer	Loss of power output, blade failure (total/ partial), excessive vibration
4	Main Bearing	Vibration, Temperature	Accelerometer, temperature sensing	Bearing failure, possible rotor/ shaft/ generator damage
5	Power Output	Electrical	Optical, Current Transformer	Excessive Vibration, harmonics indicative of mechanical problems
6	Insulation Oil (WT transformer)	PD, Temperature, DGA	Optical, Acoustic, CT	Degradation of insulation-electrical short and transformer damage
7	Hydraulic System	Pressure	Pressure sensor	Failure to pitch - increased mechanical stress, reduced energy yield
8	Actuators (yaw, pitch etc.)	Current, voltage, temp, moisture, positional info.	CT, VT, temp sensor, magnetic/optical position sensing	Failure to Yaw: reduced energy yield (shutdown?). Failure to pitch: rotor over speed, or reduced energy yield
9	Generator Insulation	electrical checks	CT, VT	Shorts, overheating, possible fire risk
10	Coolant for Generator	Temperature	temp sensor	overheating of generator
11	Inverter/ Power Electronics	Power input/ output, health of device	CT, VT, electrical status signals from device	Erroneous operation of turbine
12	Mechanical Brake	Position sensing, temperature	Reed switch, optical, temp sensor	rotor over speed, excessive mechanical loading

Table 5: Overview of Condition Monitoring for Wind Turbines

The academic interest and literature on wind turbine condition monitoring systems has increased considerably in recent times. Many comprehensive summaries of the technology are available, as well as new innovations in use of data and development of algorithms for condition assessment. A review of contributions in this field of research is now presented.

2.4.1 Literature on Wind Turbine Condition Monitoring Technology

Rademakers et al. (2004) gave a high-level overview of wind turbine condition monitoring systems, briefly describing systems for the drive train, blades, pitch mechanism, generator, electrical control/ sensors, and hydraulic systems. The authors identify the stochastic loading of wind turbines as particularly challenging with regards to the diagnosis of problems. They point out that since the ratings and capacity factors of offshore wind turbines are significantly higher than their onshore equivalents, the lost revenue is significantly higher offshore, and therefore the case for CM investment is clearer from an economic viewpoint. Additionally, they argue that maintenance costs increase greatly offshore due to logistics, increased difficulty for repair and more severe weather conditions. They reported that one of the main drivers for the use of CM in onshore wind turbines is an insurance requirement, especially in Germany.

Becker & Poste (2006) summarise the recent trends of gearbox monitoring in wind turbines, with particular reference to the German insurance market. The current practice involves replacement of all roller bearings in the drive train after 5 years or 40,000 hours of operational service (whichever occurs first); unless a drive train condition monitoring system is in place: however, they identify misdiagnosis as a source of unnecessary downtime in current systems. For vibration monitoring the authors define three levels of monitoring which can be carried out. Level 1 monitoring is threshold monitoring of broadband vibration spectra, Level 2 is band-selected thresholds for variable or fixed speed, and signals are only analysed thoroughly when the signal exceeds the threshold level. Level 3 includes extensive offline monitoring using both time- and frequency-domain analysis and is suitable for identifying faults with individual components.

A distinction is made between vibration monitoring of fixed speed and variable speed machines: pole switching is used in fixed-speed generators and so these machines operate close to maximum capacity which enables signals to be captured relatively easily. In variable speed machines (i.e. DFIGS) the rotational speed varies much more and this influences the measured vibration: the specific vibration excitation frequencies vary with wind speed and this causes a 'blurring' of the data. Other problems are: difficulty in obtaining consistent onshore readings due to gusting, the effect of control parameters, and micro variations in individual wind turbines having implications on vibration signals. This means that vibration sensors and diagnosis algorithms would have to be tuned for each individual turbine.

Some further insight into the recent trends in the WT CM industry was provided by an industry article (Anon, 2005). The article highlights that faults in mechanical systems are indicated by hot spot temperatures, vibrations and accumulation of debris in lubricants. It identifies vibration, acoustics, and strain measures as indicators of condition in rotor blades. For monitoring of gears and rolling element bearings, the systems described are based on vibration monitoring. The blade CM systems are characterized by optical strain measurements, some of which are installed at manufacture, however retro-fits are possible.

A snapshot of the state of the art in WT CM systems is provided by Hyers et al. (2006). The authors begin by stating that the economic case for CBM for onshore conditions is unproven, and that often a 'run to failure' policy combined with inspection may be the most economically justified maintenance approach. The case for CM systems is made by highlighting the characteristics of future offshore wind farms such as larger machines and costlier components. The components identified in the paper as candidates for CM are drive-train components (mainly generator, gearbox and associated bearings), rotor blades and electronic sub-systems. It is noted that the paper was published after the key components featured in this thesis were identified: however the same conclusions have been reached. This corroboration with the findings of domain experts adds significant weight to the assumption in this thesis, that these identified components are the most important. The reason Hyers and colleagues identify these particular components are firstly, the failure frequency and secondly, cost of replacement.

The main hurdles for take-up of CBM en masse are twofold. On the one hand, damage prognosis methods based on CM information are still in development and require refinement to increase prognosis accuracy, to avoid large numbers of false positives. These are mainly based on 'physics of failure' models whose parameters are updated via CM information. In this case some synergies with military research may be exploited, particularly helicopter rotor blade modelling. Related to this is reliability of the CM sensors: again this is an area of ongoing research which may be addressed via use of emerging sensor technologies. The second hurdle is the 'value proposition' i.e. economic justification. It is this topic which this thesis will address.

Hameed et al. (2007) provided a highly comprehensive review of fault detection methods for condition monitoring of wind turbine components. They outlined existing methods such as vibration analysis and oil analysis for drive-train components, thermography for monitoring of electronics and electrical components, physical condition i.e. visual inspection, strain measurement for blades, monitoring of process parameters such as control system parameters and finally performance benchmarking of the whole turbine. They argue that although the initial investment costs of condition monitoring are high, the benefits outweigh the development and implementation issues, commenting that: "... the continuous production of power without any breakdown offsets this investment cost substantially". It is noted that the authors provide no analytical results to underpin the validity of this assertion. However they also note that the investment cost of the CMS is high compared to lost production yield: so reduction of maintenance costs and component damage through use of CM are an important enabler.

Sanz-Bobi et al. (2006) developed a system supporting predictive maintenance of a wind turbine based on artificial intelligence techniques called SIMAP. The approach seeks to link maintenance with factors such as weather state, machine stress and hours in service. The main components of the system are 'normal behaviour' models based on neural networks, a diagnosis module based on a fuzzy expert system and an automated maintenance scheduling tool. It is interesting to note the number and nature of parameters used as input to the ANN (artificial neural net), with many autoregressive terms included. This suggests that the authors lack knowledge about the interactions which affect component health, since the ANN is essentially a 'black box' approach for modelling variable interdependency. The rules within the expert system have to be developed with extensive data sets and expert judgement. Additionally, some of the suggested maintenance effectiveness metrics, based on level of equipment recovery after maintenance, are highly subjective and turbine-specific.

Finally, the work of Sharpe, Infield and Leany underpinned development of a methodology to analyse WT SCADA data to enhance condition monitoring diagnosis accuracy. One interesting paper on this topic (Leany et al. 1999) outlined a set of condition monitoring techniques based on standard 10-minute performance data widely available from the wind farm SCADA system, with the aim of detecting deterioration and specific faults. The methods take account of site-specific factors, such as complex terrain, which need to be included for accurate performance evaluation. The factors affecting WT performance mentioned are meteorological, physical, terrain roughness, obstacles, topography and wakes. These factors are taken account of in the proposed turbine performance analysis model, which is based on at least one year of meteorological data so that long-term wind speeds for all wind directions can be deduced. It could be argued, however that 1 year of data is not adequate for a wind farm application since a trend should be established based on several years of data.

Additional factors are turbine layout and power curve, which are combined with the other factors to predict the output of individual WTs and thus the whole WF. These factors are combined to create a normal behaviour model of the wind farm, which also captures spatial dependencies such as correlation of wind speeds with turbine separation distance. A technique known as Kriging is used and compared with linear regression to estimate wind speed levels at different points at the test site – the authors demonstrate that Kriging gives lower errors for long-term estimates (i.e. longer than 3 months). The analysis is done offline however the authors indicate that an online system is possible since the calculations are not prohibitively time-consuming.

The authors identify a set of problems which have a negative impact on WT availability and may increase O&M costs. These are sensor errors causing spurious readings, soiled blades reducing energy conversion efficiency, yaw errors reducing energy yield, as well as unreliability of the yaw mechanism, pitch mechanism, gearbox, clutch and generator. The authors state that analysis of fault data from the above components indicates that their failure is preceded by a general deterioration in performance over a number of months, which is an interesting conclusion and illustrates the large potential of CM systems to reduce costs via efficient maintenance scheduling. An example is given of a gearbox bearing failure which showed performance deterioration three months prior to catastrophic failure, in the form of vibration trips and high gearbox temperature. The authors demonstrate that an increase in 'power turbulence' or variation of the output power can be an indication of bearing failure.

It can be seen that a fairly modest amount of research effort has been devoted to understanding of factors which affect wind turbine performance, and development of methods to increase diagnosis accuracy of condition monitoring systems. This is somewhat surprising given the growing prominence of wind farms in the worldwide generation mix. The rest of the existing body of literature on WT CM focuses mainly on development of methods for rotor blade monitoring. Burnham & Peirce (2007), Blanch & Dutton (2003) and Rumsey et al. (2008) all consider acoustic emission as a novel tool for CM of blades. Each of these three independent streams of research is at the early stages of development. Castelitz & Giebhardt (2005) use the power output of individual WTs to detect imbalance in the rotor, while Jeffries et al. (1998) employ the power spectral density for the same purpose. Finally, Ghoshal et al. (2000) focus on vibration response of pizoceramic sensor patches bonded to the blade surface for condition estimation.

Other WT rotating elements such as gears and bearings receive less attention in the literature than rotor blades. One reason for this is that algorithms for condition estimation of rotating elements have already been extensively researched. However, the main application is for the case of systems with operation at a near constant rotational speed (see Carden & Fanning, 2004) such as aero engines and steam turbines. The variable speed operation of a wind turbine severely limits the effectiveness of these existing algorithms (see Becker & Poste, 2006). It is surprising to note the lack of research devoted to algorithms specific to the variable speed operation of WTs.

One piece of research which attempts to address this problem (Jianyu & Lingfu, 2007) develops a method which identifies characteristic defect octave frequencies, which do not vary with rotational speed. This is because the expressions for these octave frequencies are purely dependent on bearing geometry. This approach may enable classification of WT bearing faults despite variable speed operation: however this is the first paper to propose such an approach. Therefore, it remains to be seen how effective the implementation will be on a real system as opposed to the test system evaluated by the authors.

The Conmow project (see Wiggelinkhuizen et al., 2007) was run for over 4 years with the goal of improving CM algorithms for the WT drive-train (rotor, gearbox and generator) but a lack of fault incidences over the period of the project resulted in very little novel output from this work. Wilkinson & Tavner (2004) illustrate a test rig for development of fault-finding algorithms for the WT drive-train. Again, the work is at the very beginnings of development.

It is observed that much of the recently proposed advanced sensing and diagnostic capability discussed is at a relatively low level of technological maturity. Furthermore, as previously discussed, the economic case for CM is even less clear than the technical case. This area of research, to estimate the economic benefits of WT CM, has received a growing amount of attention in recent years. It is explored in the next section.

2.4.2 Techno-Economic Analysis of Condition Monitoring

Wind farm operators and academics have only recently begun to understand the importance of wind farm operation and maintenance policy and associated operational issues. This is reflected in the papers published since 2006 which are very specifically focused on determining the value or discussing the effects of adopting certain wind farm maintenance policies. Most of these papers mention the importance of quantifying the economic value of WT CM or include models so that a CBM policy can be benchmarked against other maintenance policies.

Giebhardt et al. (2007) discuss economic and technical aspects of CM in the offshore case. The authors point out that although availability for modern wind turbines is high (typically 97%), the annual frequency of failures has increased significantly as machines get larger: however this has a limited effect onshore due to relative ease of repair. Offshore conditions may have a large negative impact on WT availability, with logistics being a major factor. Some proposed installations located 50km to shore could pose problems, which combined with less frequent maintenance and hostile offshore environment, could reduce availability to as low as 65%. This is broadly similar to observed availability of the Scroby Sands offshore wind farm (Scroby Sands, 2006) in the second year of production, particularly during winter months.

The cost-intensive nature of offshore maintenance, due to use of specialised heavy equipment, is highlighted by the authors (Giebhardt et al., 2007). The main traits of different maintenance policies are summarised: breakdown (reactive) maintenance is discounted because of unacceptably lengthy resultant downtimes offshore, reinforcing the assumption in this thesis that it should not be considered. Periodic maintenance is criticised for its inefficiency, since components are not used for the whole useful life, and the process is highly weather dependant. CBM is the focus of the rest of the paper: the two main challenges are use of CM information to estimate remaining life, and knowing when to trigger maintenance actions. The authors assert that more development is required particularly to improve the condition estimation algorithms, calling into question the robustness of WT CMS and suitability to offshore deployment. However, there are no calculations underpinning the assertions of the authors, for example the impact of low reliability on offshore yield.

A discussion of CM techniques follows: the main points yielded from this are a lack of empirical data, and thus limited collective experience of different failure modes (since operators are reluctant to share information). The large number of possible failure modes on the drive-train is complicated by different operational conditions which change the vibration characteristics of the drive-train, making fault diagnosis difficult. Despite the practical difficulties highlighted by the authors, the possible scope for performing maintenance according to significance of faults would result in optimised maintenance, which may make the CMS capital outlay worthwhile. Again, this assertion is not supported by any kind of calculation of the techno-economic benefit of WT CM.

In terms of actual quantification of WT CM benefit, the study by Ribrant and Bertling (2007) aims to show how use of condition monitoring systems for improved planning of maintenance actions can result in more cost-optimal operation. The authors distinguish between corrective maintenance (post-failure) and preventive maintenance (pre-failure). Preventive maintenance is further broken down into scheduled and condition-based maintenance. Reliability-centred asset management (RCAM), i.e. the concept of developing RCM into a quantitative approach, is suggested as a suitable framework for evaluating the impact of various maintenance policies for WTs. Life-cycle cost analysis (LCCA) and present value (PV) calculations are used alongside this in order to quantify the economic lifetime benefit of utilizing a CMS. Data are presented regarding maintenance policies and other operational information from two wind farms: Olsvenne 2 in Gotland, Sweden and Kentish Flats in the UK. The data presented from Vattenfall regards scheduled maintenance: minor maintenance requires 4 hours labour and needs 2 people, while major maintenance requires 7 hours and 2 people. In each case, the cost per hour for a Vestas technician is €54. Scheduled maintenance at Kentish Flats costs €750 per day per person. Unscheduled maintenance costs are €850 per day per person.

The main conclusions of the paper are that a decrease in corrective (i.e. breakdown) maintenance is needed in order to justify the CMS – a highly intuitive conclusion. In terms of quantification, the authors conclude that availability would have to increase by 0.43% annually to cover the CMS costs. Alternatively, 45% of corrective maintenance needs to be 'displaced' by preventative maintenance. No further information is given regarding failure rates, downtime or availability, possibly due to the commercially sensitive nature of the data. Additionally, very little detail is given on the models used to calculate the results. This lack of transparency casts some doubt on the yielded results.

Andrawus et al. (2006) had produced a paper independently of Ribrant and Bertling which used a near-identical conceptual approach, but provided much greater transparency in terms of presentation of their model. The authors compiled detailed costs and extracted sub-component failure rates from 6 years of wind turbine SCADA data, with the goal of deciding a suitable maintenance strategy. A reliability-centred maintenance exercise was conducted to identify the key operational components. Asset life-cycle analysis was used to carry out a study into the economic viability of the system. Finally, Monte Carlo simulation was employed to introduce uncertainty into key variables. Little detail was given on the analytical aspects, for example the range of failure rates considered was not discussed or explicitly stated. This approach suggested that, for the conditions evaluated, a Condition Based Maintenance (CBM) strategy is the most cost-effective option. The total savings of £180,152 were discounted using net present value, and equate to an annual saving of £385 per turbine over the 18 year life cycle of a 26 turbine onshore wind farm.

Even for the idealised case of a perfect CM system considered by Andrawus and colleagues, these savings are very small and cannot be contextualised since only one scenario of reliability level and downtime is considered. Another drawback of the approach in this paper is the fact that only two failure modes are considered (gearbox and generator failure). This is because the reliability data are taken from a single wind farm which only experienced these two failures. The research in this thesis has attempted to bridge this gap by using WT reliability figures over large populations as opposed to individual wind farms. A further assumption made by Andrawus et al. is that the CM system can mitigate all failure modes experienced by the wind farm. This presents an idealised and hence optimistic picture of the cost-effectiveness of the CMS. This assumption is prevalent in all the economic evaluations of WT CM which have been published until now, excepting the author of this thesis. The models presented in this thesis challenge this idealistic assumption by modelling imperfect CM-based diagnosis, i.e. not all failures are caught.

The same authors (Andrawus et al, 2007) outlined the principle of maintenance optimisation with application to wind turbines. The authors highlight the fact that RCM, while a useful engineering approach, is qualitative. Therefore they explore methods to obtain quantitative results in order to compare different maintenance approaches for WTs. Two methods are summarised for this purpose: modelling system failures (MSF) which resembles reliability analysis with a solution obtained via MCS rather than analytically. The second method is based on delay time maintenance model, where the 'time to next failure' is based on the Homogeneous Poisson Process model. The paper also discusses the data requirements of the approaches and gives an example of a WT reliability block diagram, although no results are included.

The strength of the approach presented by Andrawus and associates is its highly detailed RCM-style analysis of the WT system to the sub-component level, which will be specific to the type of turbine analysed. However this approach also has some limitations which could dispute the validity of the conclusions reached by the authors. First of all, the lack of consideration of environmental factors such as weather conditions represents a simplification of the real case, where maintenance is subject to strict weather constraints. Secondly, as metioned previously, the models assume CBM is 100% effective which is a highly disputable assumption. Furthermore, the authors do not indicate how imperfect CM diagnosis could be included in their framework.

The final issue relates to simulating the process. There is no mention of how multiple machines are accommodated which implies that parallel simulation will have to be employed. This is one area of commonality between the work of Andrawus et al. and that contained in this thesis. Although the authors claim their approach is less data-intensive than other methods, they still need substantial SCADA records to perform their analysis – this implies a retrospective element, so offering limited value for projections of future wind farms. Again this contrasts with the analysis presented in this thesis, which focuses on utilisation of large population samples of reliability data which are available in literature (see section 2.1.4). This has the added advantage of providing a more representative sample of failure rates and failure modes.

Although a growing body of research now exists to address the economic aspects of condition monitoring, many of these approaches do not take adequate account of all the factors involved, and many have unrealistic data requirements. Furthermore, the number of published quantitative studies is very low, and those that are published present specific case studies rather than an overall methodology which can be applied to any wind farm. The underlying questions posed in this thesis regarding cost-effectiveness of wind farm CMS are still largely un-answered.

2.5 Wind Turbine Maintenance and Economics

In this section, research on wind farm O&M and economics are summarised: this represents a significant addition to the literature presented on technical aspects of CM. The body of work focusing on general maintenance and economic issues for wind farms is highly relevant for this thesis, since a techno-economic analysis is proposed.

In this field it is impossible to ignore the contributions of the research groups at the Energy Research Centre Netherlands (ECN) and Delft University of Technology. Rademakers et al.

(2003a) discussed the need for research and development focusing on maintenance of offshore wind farms. The authors identified four areas where R&D was required: identification of turbine failures, models for O&M cost, optimisation of O&M and the need for field data, and the added value of CM as well as its limitations. Data were presented showing O&M costs, service contracts and overall failure rates. Additionally, it was illustrated that corrective turbine maintenance costs increased with turbine age, and substantial uncertainties were encountered after the 5th year due to the expiry of manufacturers' service contracts. Other factors affecting this uncertainty were turbine size and reliability, water depth, wind and wave characteristics, and distance to shore. The outputs of the work are intended to enable optimization of maintenance via design alterations or different turbine access systems. The cumulative distribution function (cdf) is utilized to introduce uncertainty into the failure rate, since the measured value is an expected (mean) value. Demonstrating the added value of condition monitoring was identified as one area of future research alongside prediction of remaining life.

A review of reliability and maintenance for large-scale offshore wind farms is compiled by van Bussel & Zaaijer (2001). Particularly interesting collections of data regarding turbine failure frequency are provided. These were formed from expert opinion, and represent a useful set of figures at the sub-component level. It is interesting to note that, while the gearbox is considered one of the less reliable components, the inverter and control failures are both assigned higher values for failure frequency. New design philosophies are suggested in order to reduce failures and downtime in large offshore wind farms, these are: reduce number of components (i.e. fixed pitch, direct drive machine), adopt modular design (to enable easier and more rapid replacement), use more integrated components, and integral exchange policy (replace entire assembly so that damaged assembly can be repaired offline).

Rademakers et al. (2003b) developed a model specifically for investigating costs, maintenance activities and downtime for offshore wind farms. Their approach consists of three main aspects: turbine failure behaviour, repair strategy and weather effects. The authors make use of Monte Carlo simulation to model stochastic input parameters such as costs and failure rate of the wind turbine. The frequency and duration of weather windows for maintenance are modelled using real data fitted to the Weibull distribution. The model was implemented in an Excel spreadsheet. Results presented in the report suggest that the failure frequency of the main components such as the gearbox, blade and generator are the factors most strongly coupled with cost.

A very insightful contribution from Ribrant & Bertling (2007) analysed failure statistics from four sources: two Swedish, one German and one Finnish. But the focus was mainly on the Swedish results. The first major conclusion stated in the paper is that the WT gearbox is the most critical WT component since the downtime per failure is high compared with other components. The authors analysis of the data by turbine rating and age showed that while smaller rated WT (<1MW) failures tend to decrease over time as they 'burn in', the turbines rated over 1MW seem to increase their failure rate as they age. The authors propose that the cause of this may be higher fatigue loading for WTs than for other rotating machines such as steam turbines.

The authors aimed to identify the most critical WT components by examining the failure frequency and downtime per failure of the individual sub-assemblies, with the overall objective of finding a balance between maintenance frequency and availability. The authors go on to describe the data recording procedures for the various problems such as turbine reset, inspection or repair. Information was displayed regarding percentage sub-component contribution to failure rate and downtime. The mean annual failure rate for a Swedish turbine was found to be 0.402 failures per year, which is very low compared with other sources, while mean downtime was 130 hours per year. However the authors stated that downtime for three components: drive train, gearbox and yaw system, was between 250-290 hours.

A more detailed study was performed on gearbox failures of the Swedish turbines, illustrating the downtime related to each gearbox failure mode. These were as follows: bearings 601 hours, gear wheels 378 hours, oil 36 hours, seal 30 hours, not specified 299. The bearing failures almost always required a gearbox replacement, while around 59% of the 'non-specified' failures required a gearbox replacement. The cause of most of these failures, as state by the authors, was wear/ fatigue. The long downtimes attributable to gearbox and drive train problems are associated with availability of spares and suitable crane vehicles.

Juninger et al. (2004) project future costs of offshore wind farms, based on theoretical cost reductions achieved through factors such as mass production of large components and high utilisation of specialised installation vessels etc. One quantity of interest identified by the authors is the offshore turnkey investment which was in the range €1.2 - €1.85 million per MW installed capacity. This makes for an interesting comparison with onshore costs of €0.8 - €1.1 million for MW. Actual turbine costs as a function of capital cost were between 30% - 50% for offshore, and 65 - 75% for onshore.

The CORLEX project, which aims to reduce costs and extend life of offshore wind farms is presented by Bhardawaj et al (2007). They developed a risk-based decision model to maximise the net present value (NPV) of maintenance actions (e.g. run, repair or replace) for offshore wind farms. Expert opinion determined which WT components had an unacceptable level of associated risk, so that these components were the focus of subsequent analysis: however the paper included a single component application of the method to the tower structure. The remaining life of the structure was estimated via a deterministic equation, however the inputs were sampled for a distribution using Monte Carlo methods: this was used to calculate the annual probability of failure as the structure ages. A linear programming optimisation algorithm was applied to optimise the maintenance actions in terms of NPV maximisation. The main weakness of this approach is the focus on the ageing period at the end of asset life rather than normal operation which concerns wind farm operators currently. Since rotating elements age and are replaced much more frequently that the tower structure, the value of the methodology for drive-train or rotor components may be limited.

The goal of Christensen and Giebel (2001) was to predict the availability of an offshore wind farm based on contributions from scheduled and unscheduled maintenance actions based on data from the 150MW (75 X 2MW) Rodsand wind farm. Repair actions were dependent on availability of a suitable vessel for large components and also on a suitable weather window. The parameters which determine access are defined by the authors as wind speed, wave height, temperature, ice cover, boat icing, snow, fog and visibility in general. The access model was based on a Markov Chain which captured probability of occurrence of the relevant climatic conditions needed for access to the wind turbines. The total number of weather states was 6 states: these were used in conjunction with the offshore access rules. The 6 states were based on simplification of the ½ hourly access data to 8 hour weather windows i.e. the model is approximate. If the access rules were not met then maintenance is deferred until arrival of a suitable weather window. Seasonality was not captured due to only 183 days of data being available. The authors suggest that seasonality could be captured via different Markov transition probability matrices which define the stochastic behaviour of the model.

Maintenance models were developed for preventive and corrective maintenance, which were based on combinations of deterministic and probabilistic times for the sub-events such as fault detection, mobilisation, logistics and repair. Data were given for the parameters however no indication was given of how these were estimated. For the bi-annual preventive maintenance the parameters were 16 hours for deterministic service time however when the probabilistic parameters were added (detection, logistics and mobilisation) this was around 27 hours. For corrective maintenance the downtime appeared to be modelled very similarly: however time to failure event was modelled as a Gaussian distribution with mean of 120 days and σ of 5 days.

Research quantifying cost of operation and maintenance is certainly more developed than the specific case of techno-economic analysis of condition monitoring. One of the main reasons for this is that it is more difficult to capture deterioration behaviour, and the analysis has to be at the sub-component level for a cost/ benefit analysis to be conducted. However the techniques are relevant because both cases are essentially a quantitative evaluation of operating policy.

2.6 *Chapter 2 Summary*

It is apparent that although CM systems for wind farms are widely deployed, the operators of those wind farms remain unsure if condition-based maintenance is an appropriate operational policy for their assets. This is because of a combination of the perception of CBM as a complex maintenance paradigm as compared with time-based maintenance, real problems adapting existing algorithms and techniques for WT fault categorisation (especially vibration monitoring), and the more general difference in operational characteristics of wind farms as compared to thermal plant.

However, it has also been shown that there are persuasive arguments for CBM applied to WTs, not least the probable future growth of offshore wind farms. The main problem is that the value of such an approach has to be demonstrated – otherwise it is all too easy to keep using more traditional approaches to maintenance, such as periodic maintenance.

Quantitative models can be developed to capture the characteristics of operation, maintenance and economics of wind turbines and wind farms. The models proposed in this thesis circumvent the problems inherent with the other published models. The most notable of these is the simplistic assumption of perfect CM diagnosis which appears in other research. Imperfect CM systems will be explicitly modelled in this thesis.

The models presented in this thesis are not tied to any one data source. Rather, data of different forms and from various sources is accommodated. This is a distinct advantage over other published approaches, as wind farm operational data are sparse at the time of writing. Implicit in this fusion of data sources is the ability of this approach to enable the CM benefit to be quantified for realistic ranges of operating conditions. These include component reliability, downtime and capital and operational costs. Such studies are useful for specifying particular key enablers or 'conditions for success' for WT CM systems. Furthermore these can be specially adapted to create particular conditions of interest. For example, offshore conditions can be simulated and the impact on the cost-effectiveness of CM evaluated. The flexibility offered by this approach provides insight over and above the existing research on this subject, as described in this section.

The methodology presented in this thesis provides valuable insight into wind farm maintenance policy decisions. More than this, it will become increasingly necessary for wind farm operators to understand how best to operate and maintain wind farms. This will be especially pertinent in the coming decades as large numbers of wind turbines come out of their warranty period and responsibility for O&M is (generally) transferred from manufacturers to utilities.

The need for the research presented in this thesis has been established in this chapter, with reference to the shortcomings of other work in this area. This thesis is concerned primarily with investigating techno-economic aspects of condition based maintenance: therefore the models which are developed have to satisfy very specific requirements. These requirements are discussed in section 3.

2.7 Chapter 2 References

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3 Wind Turbine Operational Model Requirements and Selection

This chapter of the thesis begins by breaking the problem of quantifying the techno-economic benefit of WT CM into three main aspects. The three aspects are: wind turbine component deterioration and failure, wind speed and energy yield, and asset management and maintenance policies. The chapter proceeds by investigating which methods are suitable to meet the technical modelling requirements of each of these three aspects. After defining what the capabilities of the models should be, the rest of this chapter compares the characteristics of different models which could be applied and assesses their suitability to this particular application of quantifying the techno-economic benefit of WT CM. Through this process, the methodology used in the rest of the thesis is defined.

3.1 Definition of Model Framework

In order to achieve the objectives of this research, it is necessary to define the requirements of the modelling framework so that suitable models can be selected and developed for this application. This framework was developed within the first year of this research after consultation with industrial research partners, and consists of three key aspects which should be modelled. These are shown in Figure 6 along with possible inputs and outputs.

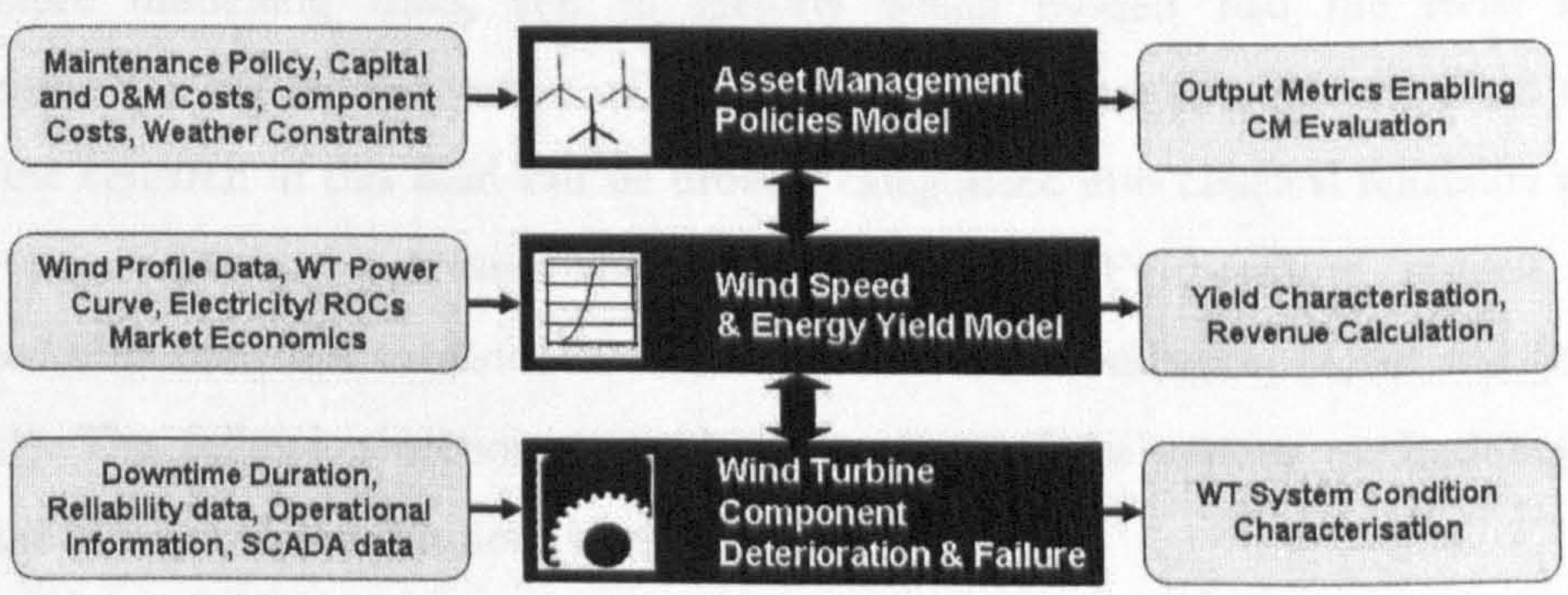

Figure 6: Key Model Requirements with Possible Inputs & Outputs

Wind farm economics depend on a multitude of factors. However they can be boiled down to capital expenditure (CAPEX) and operational expenditure (OPEX). CAPEX is already fairly well quantified for many projects, however OPEX is less well understood. Additionally, the wind farm operator has far more control over OPEX in the form of asset management policies, which consist mainly of what sort of maintenance to perform and when to perform it. Therefore, modelling of asset management is essential to any study: hence its inclusion in Figure 6. The primary revenue stream for a wind farm is electricity sales based on energy yield and, in the case of the UK, revenue generated from the renewables obligation (RO) system, which is discussed later. This is the reason for inclusion of wind speed and energy yield modelling.

Finally the reliability of the wind turbine sub-components determine not only the availability of the system to generate electricity, but the incurred costs for maintenance and replacement of components which can have a very significant impact on the economic performance of a wind farm. Potential modelling solutions to each of the three model aspects are discussed in the following sections.

3.2 Models for Deterioration and Failure of Wind Turbine Components

A comprehensive review of literature in the area of deterioration and failure modelling of engineering systems was conducted throughout the duration of this research. The aim of this exercise was to gain a detailed understanding of models which had been applied in similar infrastructure modelling tasks, and to identify which models had the most suitable characteristics for the representation of deterioration and failure process of a wind turbine. Most of the research in this field can be broadly categorised into classical reliability models, Markov chains, Markov processes and time delay models. Furthermore, models can be categorised into analytical methods and methods based on simulation (Allan and Billinton, 1992, p11). The following sections provide a summary of the various methodologies and identify the influential contributions in each area.

3.2.1 Analytic Classical Reliability Model

A classical reliability model characterises the failure behaviour of the system in question in a quantitative manner via use of probability-based models. Analytic methods require the reliability to be a mathematical expression which is solved using direct or numerical methods, depending on the model complexity. Failure rate $\lambda(t)$ of a population of units (the number of failures ($\#F_t$) per unit ($\#N$) in the time period examined) is a pre-requisite for application of probabilistic models (equation 3). Probability density functions (PDFs) are used to capture the failure behaviour based on the failure rate: commonly used distributions for modelling failure are Poisson and Weibull distributions. They are often used in theoretical texts because they can capture different stages of equipment life. However the most widely used distribution is the exponential distribution, which can only be applied if the failure rate is constant over time, as assumed in this thesis.

This assumption of constant failure rate is often made in studies without much justification or discussion of the consequences. The primary reason a more complex expression is not used in this thesis is that wind turbine reliability data are dominated by newer machines installed in recent years. The theoretical increase in failure rate as the WT approaches the end of the design life (~20 years) has not been reached and so data characterising these effects is currently unavailable. The key consequence of the 'constant failure' assumption for this thesis is that this model should only be used to characterise the early to middle life of a wind turbine. It should not be used to evaluate end of life effects.

Assuming constant failures, the probability of a component surviving for time t, which is called the reliability function $R(t)$, is related to λ by equation 4.

$$\lambda(t) = \frac{\#F_t}{\#N} \tag{3}$$

$$R(t) = e^{-\lambda t} \tag{4}$$

A very important property of the exponential distribution applied to reliability is shown in equation 5. That is the probability of failure *U(t)* in any constant interval of time *t* is the same as the probability of failure on the condition that the component has survived up until the time period of interest, $U_c(t)$. In other words, the failure probability is independent of the previous operating time and is dependent only on the length of the current time interval *t*. The main assumption here is that the probabilities of failure both in the past (a posteriori) and the future (a priori) are equal, which is only true if the failure rate is constant, and not increasing or decreasing (Allan & Billinton 1992, p 184).

$$U(t) = U_c(t) = 1 - e^{-\lambda t} \tag{5}$$

A very useful way of approximating equation 5 is yielded firstly by applying the Maclaurin series expansion. The result from this is shown in to equation 6.

$$U(t) = U_c(t) = \lambda t - \frac{(\lambda t)^2}{2!} + \frac{(\lambda t)^3}{3!} - \ldots \tag{6}$$

Examining equation 6 more closely, if it is assumed that the product of λ and *t* (i.e. the numerator of each term) is very much smaller than unity ($\lambda t << 1$), then the terms of the Maclaurin series tend to approximately cancel out (opposing signs and broadly similar magnitudes) with the exception of the first term, λt. This means that expressions for reliability and failure functions are reduced to expressions only a single term of λt. This represents a simple and convenient simplification. The resulting expressions for unreliability and reliability are shown in equation 7 and equation 8 respectively. These correspond directly to equation 5 and equation 4 respectively.

$$U(t) \approx \lambda t \tag{7}$$

$$R(t) \approx 1 - \lambda t \tag{8}$$

By far the best way to appreciate the adequacy of this approximation is to plot the functions themselves. This has been done for R*(t)* in Figure 7 for two different values of λ. If the plot values are closely matched for each value of λ then the approximation explained above is adequate. Figure 7 very clearly shows that for small values of t and λ (left hand side of plot), equation 7 and equation 8 are perfectly adequate for characterisation of component failures. It is emphasised that this is only true if constant failure rates can be assumed.

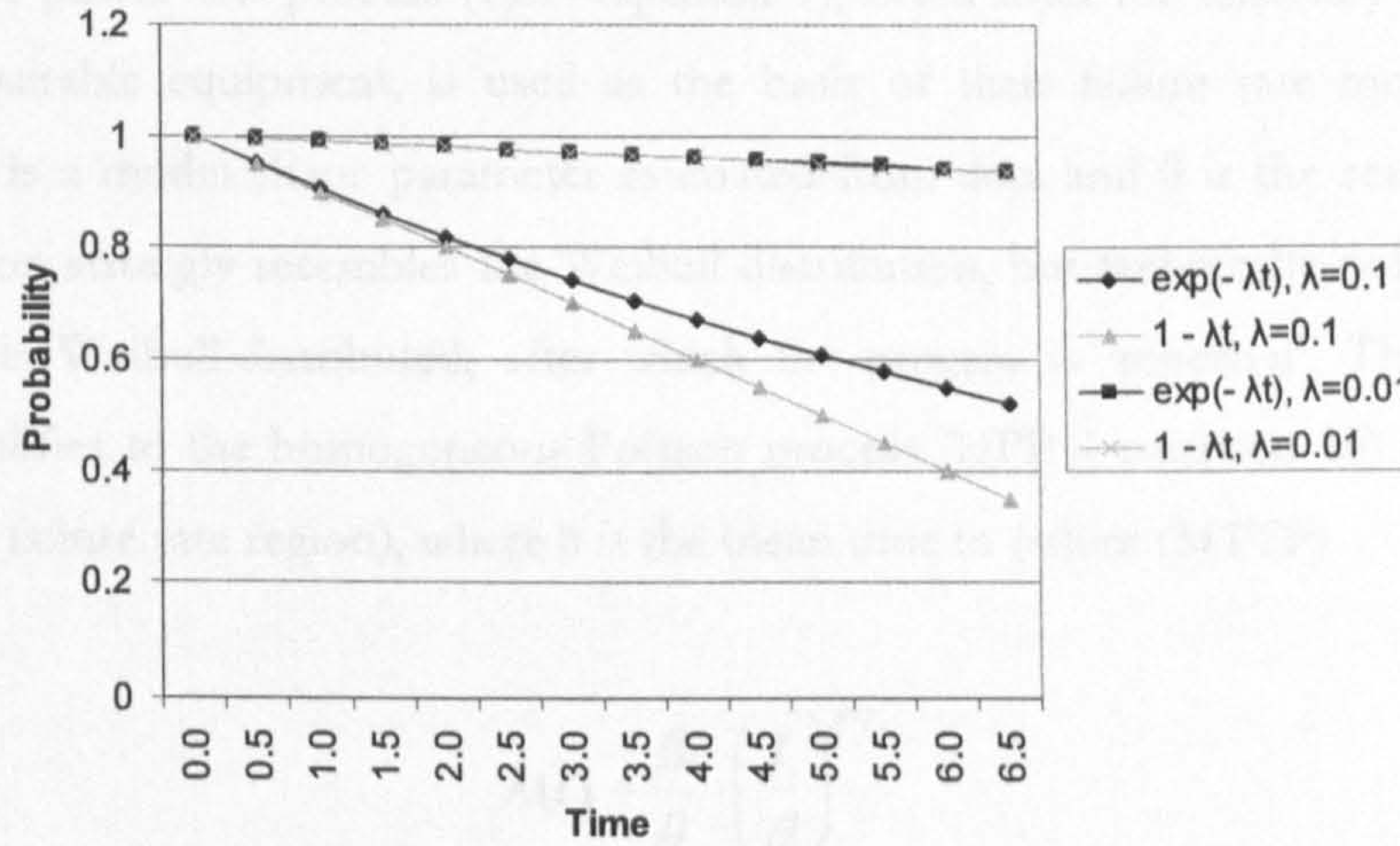

Figure 7: Plot of Exponential Reliability Function $e^{-\lambda t}$ vs. Approximate function $1\text{-}\lambda t$

It follows that reliability or unreliability in a specific time period can be very easily evaluated by using the simplified expressions in equation 7 and equation 8. This is achieved by substituting in values for the failure rate λ (which is estimated by applying equation 3 to a data set) and deciding on the length of evaluated time period t. A very simple example can be demonstrated by considering a wind turbine generator with annual failure rate of $\lambda = 0.1$. We assume a constant failure rate over time. If the probability of the component being reliable was to be calculated for the duration of a single year, then t=1 and according to equation 8 the probability of the generator being reliable for one year is:

$$R(1) \approx 1 - 0.1 \times 1 = 0.9$$

The above method is adequate for systems where initial problems after installation or age-related failures are not of interest: however it can be rather limited in scope. In particular, if the time-varying characteristics of reliability are of interest then the exponential distribution cannot be applied since the probabilities are no longer constant in time. In this case more complex expressions are derived.

Tavner and colleagues (2007, 2006a, 2006b) comprehensive analysis of wind turbine failure trends constitute the state of the art in this field. They have produced numerous influential contributions, mainly based on fitting probability distributions to wind turbine failure statistics. The power law process (PLP–equation 9), often used for reliability modelling of complex repairable equipment, is used as the basis of their failure rate model $\lambda(t)$. The parameter β is a model shape parameter estimated from data and 0 is the scale parameter: this expression strongly resembles the Weibull distribution, but technically only the time to first failure is Weibull-distributed, after which the process is 'renewed'. The power law process simplifies to the homogeneous Poisson process (HPP – equation 10) if β=1 (i.e. in the constant failure rate region), where θ is the mean time to failure (MTTF)

$$\lambda(t) = \frac{\beta}{\theta} \cdot \left(\frac{t}{\theta}\right)^{\beta-1} \tag{9}$$

$$\lambda(t) = \frac{1}{\theta} \tag{10}$$

Based on these models, the question of how weather conditions influence wind turbine reliability was investigated by Tavner and colleagues (2006b). A dataset comprising Danish turbines from 1994 – 2004 was considered, with the population size changing from just under 2000 in 1994 to just over 1000 in 2004, probably due to re-powering projects. Because of the large population considered in the database, various WT architectures and ratings are included within the sample. The data time resolution of one month impacts on the subsequent models since gusting and turbulence cannot be captured, however large weather systems cover entire countries and thus macro-scale seasonal impact on failures can be captured. An index called the wind energy index 'WEI' was used instead of actual wind speed, and the authors make the assumption that the turbines are evenly distributed throughout the country.

Plots of the WEI and failure rate, λ, show suggestion of coupling between weather effects and equipment failures. More rigorous proof is sought by application of cross-correlation functions and spectral analysis, which are both discussed in some detail. The main result shows the cross correlation coefficient for WEI and λ plotted for individual wind turbine sub-assemblies. The components considered to have significant coupling were: whole WT 44%, generator 46%, Yaw 31%, mech. control 29%, brake 25% and hydraulics 25%, although there appeared to be no formal rules for deciding what constituted significant correlation. This means that during high winds the probability of failure of these WT components increases, with negative implications for energy yield. The main drawback of the approach is that significant high-resolution events such as gusting are not captured in the models due to the low time resolution.

The authors' main aim in (Tavner et al. 2007) is to understand historic reliability of modern WTs and to extract information so that future large WT reliability can be predicted, taking account of effects such as design, configuration, time, weather and maintenance policies. The size of the WT population examined (6,000 Danish WTs, 20,000 German WTs) and the time interval of the data (10 years) were considered statistically important since the larger these are, the higher the probability of failures occurring on each WT during the time interval. The two proposed models are the power law process (PLP), which can model any stage of the characteristic 'bath-tub' reliability curve, and the homogeneous Poisson process (HPP). These models were fitted to the data using maximum likelihood estimation and tested using the χ^2 statistical check. The model outputs show a number of interesting features: decreasing failure rates with time, higher failure rates for German turbines, and a monthly periodicity which the authors attribute to weather effects.

The authors apply the HPP model to the individual WT assemblies and observe that in Germany the main contributors to the overall failure rate are electrical control (i.e. grid/ electrical system, yaw systems, and mechanical pitch system), which may be due to the increased power electronics involved in variable speed drive technology. This seems to be contrary to the widely-held belief that the gearbox is the major cause of WT failures: however the mean time to repair for the gearbox is extremely high compared to MTTF for electrical failures, due to the physical problems associated with replacement or repair of WT nacelle components. German subassemblies show annual failure rates as follows: gearbox 0.100, blade 0.223, generation 0.1196, electrical controls 0.223 and grid/electrical system 0.341. The PLP model was used to plot reliability growth curves, with overall long-term values of 0.7 failures per year for Danish WTs and 1.3 failures per year for German WTs. The factors affecting this are the different age of the Danish and German populations, and the different sizes of the populations: the German turbines are significantly newer, and the German population was 8 times larger than the Danish population in 2004. Finally, the authors proved that WTs are more reliable than US diesel units, equally reliable as UK CCGT units, and in 10 years may be as reliable as US steam turbines.

The main issue examined in (Tavner at al. 2006a) is how the configuration of the WT generator and converter in different design concepts affect WT reliability. Quarterly data taken from the windstats database (2004) shows that WT failure rates are decreasing over time. This contrasts with data from LWK (Landwirtschaftskammer, Schlewig-Holstein, 2008) in Germany which shows an increasing failure rate (possibly attributable to differences in the population age). The LWK data had enough detail to enable a direct reliability comparison of three WT concepts: fixed speed with gearbox, variable speed with gearbox, and variable speed direct drive (no gearbox: synchronous generator). The homogeneous Poisson process model was applied to the subassembly reliability data and conclusions drawn from the resulting comparison. The main conclusions were that direct drive systems are less reliable than models with a gearbox because the potential increase in reliability due to elimination of gearbox failures is cancelled out by increased generator, inverter and electrical system failures. Overall reliability will also be affected by repair times and in this sense direct drive systems may have an advantage, since MTTR for a gearbox is likely to be very much more than MTTR for an electronics subassembly: however the authors did not attempt to quantify this. This trend seems to suggest that direct drive machines will be suited to environments where repair is especially difficult, for example future offshore wind farms. The authors urge that future decisions regarding WT design concepts and procurement should be more focused on reliability, rather than solely on capital cost and energy yield capability as is currently the case.

Wilkinson et al. (2006) also analysed two wind turbine reliability databases – windstats and LWK, commenting that the main driver for increased reliability is the future deployment of large offshore wind farms. Use is made of reliability analysis (homogeneous Poisson process), failure mode and effects analysis (FMEA) and condition monitoring is proposed to mitigate various failure modes. The paper focuses on the LWK survey which consisted of one year of data, although the number of turbines is only roughly given as being in the 'tens' rather than hundreds. The main findings were: high levels of unreliability for direct drive synchronous generators, with each failure cumulatively decreasing the availability and economic performance of the WT. The reason for the high number of failures were hypothesised: larger diameter machines harder to protect from humidity resulting in insulation damage, or manufacturing flaws due to low production runs and resultant problems with standardisation of components. Another observation was that hydraulic pitch wind turbines are significantly more reliable that electric pitch.

The FMEA showed that material failure is the most common failure mode: corrosion, vibration fatigue and mechanical overload (i.e. wear-type failures). Shock failures are less common but include blade fracture and broken gear teeth. Finally a test rig to develop a CM system is illustrated however fault-finding algorithms had not been developed at the time of writing.

Classical analytic reliability methods applied by Tavner and colleagues certainly help interpret large volumes of reliability data. However if an entire analysis of wind farm operation is required, more diverse aspects need to be considered. In particular for wind farm analysis, modelling of wind turbine downtime after failure and site wind resources need to be considered. In this case analytic solutions become cumbersome and difficult to formulate. For this reason it is often discarded in favour of Monte Carlo simulation (MCS).

3.2.2 Reliability Model Evaluated via Monte Carlo Simulation

Monte Carlo simulation (MCS) methods replicate the process they seek to model by use of pseudo-random numbers, and are sometimes described as 'a series of real experiments'. Instead of finding the direct solution as per the analytical approach in the previous section, a series of trials are conducted many times to evaluate the metrics of interest. The outcomes of these trials are decided by generating pseudo-random numbers (PRN) and using these to sample the process. This approach has many advantages over analytical methods, possibly the most prominent being that many factors can be modelled without having to construct an analytic expression. The answer obtained by simulation is an estimate rather than a definite answer, the accuracy of which depends on the complexity of the system and how many trials have been conducted.

The equation for a well known PRN generator function, called a linear congruential generator, is shown in equation 11. A pseudo-random number (I_t) is generated based on the previous value (I_{t-1}) and a set of coefficients which are named multiplier (A), increment (C) and modulus (M) according to their purpose in equation 11. The values of each coefficient are chosen with the aim of maximising the period of repetition of the resultant PRN series. Values adopted in this thesis are those taken from numerical recipes in Fortran (Press et al. 1992) and are as follows. A=1664525, C=1013904223 and $M=2^{32}$. These generated variates should always be used in a series and not split up into 'parallel' streams of simulation since this would nullify the randomness of the generator (Press et al., 1992).

$$I_t = (A \times I_{t-1} + C) \bmod M \tag{11}$$

For the purposes of the MCS in this thesis, a number between 0 and 1 is required (PRN_t). This is obtained by dividing I_t by the modulus M (shown in equation 12). It can be seen that the latest PRN in the series is related to the previous calculation of the pseudo-random series I_{t-1} as well as the coefficients A, C and M (Billinton and Allan, 1992, p376).

$$PRN_t = \frac{I_t}{M} \tag{12}$$

The initial value of the PRN series at time t=0 is known as the seed value. The method used in this thesis to set the seed is via use of the CPU clock. The current time in seconds and milliseconds is determined at the start of the MCS and the sum is used as the PRN seed.

A very simple example of MCS applied to a reliability model can be illustrated by considering again the expression for reliability defined in equation 8. By substituting values of λ =0.1 and t=1 for a wind turbine, the analytic expression for the single year reliability was calculated as 0.9. The same metric can be derived using MCS, however instead of extracting a single value for the annual reliability, several trials are conducted to arrive at a conclusion: in effect the operational process is simulated. Each trial represents 1 year of system operation.

The crux of the MCS is a comparison of the PRN and the reliability expression. By comparing the PRN generated in equation 12 with the expression for reliability in equation 8 we arrive at a rule for evaluating the reliability of the wind turbine at each trial as shown in Table 6. If the PRN is greater than the reliability expression, then the system has failed. If this condition is not met, it has stayed in service.

MCS Condition	Wind Turbine System Status
$PRN_t \succ R(t)$	Failed
$PRN_t \leq R(t)$	Operational

Table 6: Condition Evaluated at each MCS Trial

The number of trials needed to estimate the metrics of interest using MCS is very dependent on the complexity of the system. In the case of a single plant item with only two possible states – failed and operational – a small number of trials is adequate. This is demonstrated in Table 7 which shows the different stages to calculate the PRN, resulting in the quantified reliability of 0.9 – the same as the analytic case. The initial seed value of 58 was calculated by taking the seconds and adding the milliseconds (8+50). To quantify the reliability, the average of the simulations is taken i.e. the reliability column is summed and divided by the number of trials (9/10). This is a similar calculation to that of estimating the failure rate in equation 3.

Trial	I_k	$(A \times I_k) + C$	mod M	I_k+1	PRN	Reliability
1	58	7816997155	3522029859	3522029859	0.820	1
2	3522029859	4.74684E+17	653498816	653498816	0.152	1
3	653498816	8.80758E+16	738787520	738787520	0.172	1
4	738787520	9.95707E+16	2257585088	2257585088	0.526	1
5	2257585088	3.04268E+17	12522176	12522176	0.003	1
6	12522176	1.68769E+15	526802369	526802369	0.123	1
7	526802369	7.10002E+16	1532975304	1532975304	0.357	1
8	1532975304	2.06608E+17	4175682528	4175682528	0.972	0
9	4175682528	5.62781E+17	953338752	953338752	0.222	1
10	953338752	1.28487E+17	688650624	688650624	0.160	1
				Quantified Reliability		0.9

Table 7: Monte Carlo Simulation of System Reliability

Clearly very few systems are as trivial as those presented so far. For example, they may contain multiple components, or require multiple states to represent them. Additionally wind turbines are repairable systems and aspects of their operation are coupled strongly with wind speed. Therefore, when MCS has been used in wind farm reliability evaluation, other methods are often used in tandem to capture these other key aspects. In this area, the recent work of Negra and associates (2007a) has been the most insightful from the viewpoint of the wind farm operator. Negra has used his extensive knowledge of the offshore wind sector to examine the technical implications of wind farm reliability. The focus is on electrical aspects of wind farms but a number of environmental and mechanical factors are explored.

Negra's approach (2007a) comprises a planning and operations tool for offshore WF reliability based on MCS. Nine areas of importance were identified from the literature for offshore wind generation reliability assessment. These were: Wind speed simulation, wakes modelling, WT technology, offshore environment, different wind speeds within the WF site, power generation grid, correlation of WT outputs, grid connection configuration and hub height variation. The wind speed model is based on a Markov Chain, with data partitioned at 1m/s intervals. In order to preserve the annual seasonal variations in wind profile, the authors defined a separate model for each of the 12 months in the year. It is not explicitly stated if the model is discrete or continuous in nature, however since MCS is being applied this suggests the wind model is discrete-time.

Some interesting comments are made by the authors regarding reliability modelling of WTs in the offshore environment. Firstly they state that the mean time to repair the WT will increase significantly compared to the onshore case, due to bad weather, time to reach the wind farm and access problems offshore. Secondly, and perhaps more interestingly, they suggest that the failure rate of the WT components will increase due to the harsh offshore environment. These comments are highly insightful, since the authors are involved in operating existing large offshore wind farms in Denmark.

Data used by the authors, and estimated from seven years of data from Horns Rev offshore wind farm indicate a WT mean time to repair of 490 hours per year (~20 days) and a failure rate of 1.5 failures per year, however these figures are for the entire WT and not for specific component failures. Two interesting results yielded by the authors are that the cable and connector reliability has significant impact on WF reliability: their simulations indicate a 3.5% annual loss of energy due to these failures. The overall WF availability is calculated as ~90%, however the authors indicate that this figure may be pessimistic, since 1.5 WT failures per year may be at the high end of the unreliability scale. The use of an overall WT failure rate and downtime is not appropriate for this thesis because individual components need to be considered for detailed O&M modelling. Additionally, if SCADA wind speed records are available it is not necessary to apply hub height correction (e.g. log power law) to wind speed measurements made from near sea level, as practiced by Negra and associates. Furthermore, use of a Markov chain wind model results in simplification because the state space needs to be partitioned at discrete intervals. Use of a continuous state-space time-series regression model, as proposed in this thesis, could circumvent this simplification.

Issues affecting offshore wind farm reliability were discussed by Holmstrom and Negra (2007b). These were: design and construction, operational reliability, protection and earthing and grid problems. A table presented all operational offshore wind farms along with technical characteristics such as existence of an offshore substation, rotor diameter of turbines, distance to shore, number of transmission line conductors and investment costs. The range of capital costs was €1.17M – €2.25M per MW installed capacity. The authors distinguish between reliability from two viewpoints: wind farm view and overall system view – the paper focuses on the second of these two. The authors' experience from offshore installations indicates that the electrical sub-systems of the WTs are vulnerable to the marine climate, vibration and intermittent operation. Other problems encountered are: high failure rates of electric power converters, increased frequency of lightning strikes and significantly increased time to repair for even trivial problems.

The authors discuss the need for reliability data, pointing out that the normal source for data are failure histories, and reliability studies are normally based on extrapolation of these figures. One issue with this approach is that measurements should be taken over a long time period in order to be statistically credible (i.e. adequate number of samples): however such data does not currently exist for offshore wind farms. An interim solution is to use data from onshore sites to populate initial models.

It can be seen that a reliability model on its own, while providing a good grounding for understanding of applied probability theory, is not sufficient to model the more detailed aspects of wind farm O&M. In particular, it is not suitable for modelling deterioration of multiple components and thus cannot be used for evaluation of different maintenance policies. Additionally, modelling of repair is often very simplistic i.e. one time to repair for the entire WT assembly, neglecting effects of individual component failures. Since this is a key requirement of the work presented in this thesis, more detailed modelling approaches must be considered which are capable of capturing these aspects.

3.2.3 Markov Chain

Markov chains are based on the original work of Andrey Andreyevich Markov (1856 – 1922). The basic model is rigorously defined by Romanovsy (1950) as "A simple homogeneous Markov chain with a finite number of states and discrete time". Such a clear definition is important, since the number of variants of Markov chains, and the continuous time equivalent the Markov process (discussed later), are almost bewildering in number. This may be due to the academic roots of the framework as a mathematical construction rather than a tool for problem solving: however, as an engineer the author is interested in how the method may be applied and answer real questions rather than the mathematical theories themselves.

The Markov chain is defined by the states of the modelled system and the transitions between those states, the transitions being probabilistic in nature. Considering a system with a number (n) of states (s_1,... s_n), and assuming the transitions between them are defined by probability $p_{a,b}$ where a is the current state and b is a possible state transition, then the system in Figure 8 can be defined. The state-based representation is often used to describe degradation of engineering systems, and in this thesis is applied to model wind turbines and their key sub-components.

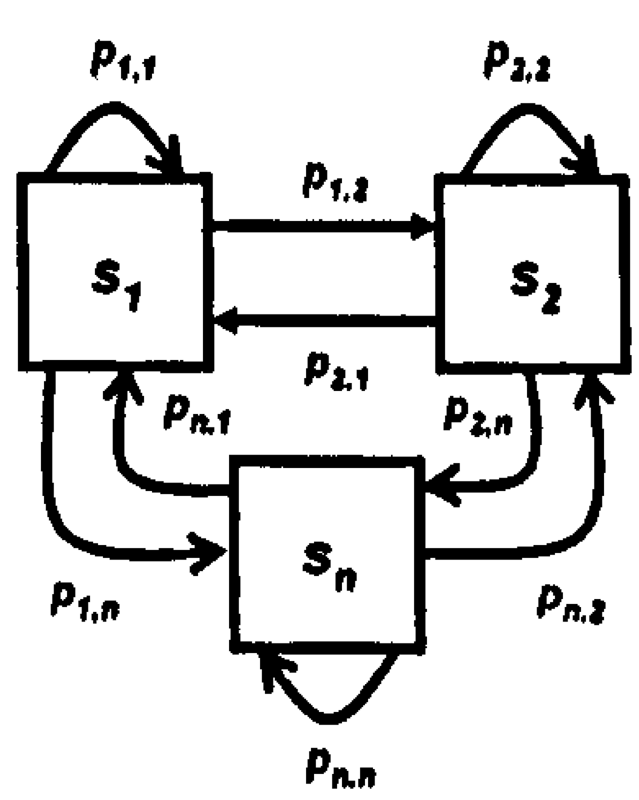

Figure 8: Generic Markov Chain

The probability $p_{a,b}$ is dependent only on the current state of the system, i.e. the system has no 'memory': this is expressed in equation 13. The chain is homogeneous, or 'stationary' which means that the transition probabilities are constant in time: however this assumption is relaxed later to allow for accurate modelling of different wind farm operating conditions (e.g. maintenance). Many other researchers have relaxed the stationary property in order to model realistic conditions - see Sayas and Allan (1996) and their modification of Markov chain transition probabilities for modelling of increased failure rate for extreme wind conditions. Another key property of a Markov chain is that all transition probabilities from one state must sum to one, as expressed in equation 14.

$$p_{a,b} = P\left(s_b, t_{k+1} \mid s_a, t_k\right) \quad k = 1,2,3.. \tag{13}$$

$$\sum_b p_{a,b} = 1 \quad a = 1...n \tag{14}$$

Taking state s_1 as an example from Figure 8, this means that $p_{1,1}$, $p_{1,2}$ and $p_{1,n}$ must all sum to one. The Markov chain transitions are often summarised via use of a matrix of the transition probabilities, which in this thesis will be called the transition probability matrix (*TPM*). The general form of this matrix is introduced in equation 15. The TPM values can be estimated from data or expert opinion.

$$TPM = \begin{bmatrix} p_{1,1} & p_{1,2} & \cdot & p_{1,n} \\ p_{2,1} & p_{2,2} & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ p_{n,1} & \cdot & \cdot & p_{n,n} \end{bmatrix} \tag{15}$$

In the case of Figure 8, every state was reachable from every other state, either directly or via other states: this property is called ergodicity (Billinton & Allan, 1992 pp265). Systems which are not ergodic contain states which cannot be 'escaped' from once entered. These states are known as absorbing states: Figure 9 shows a system containing an absorbing state, s_n.

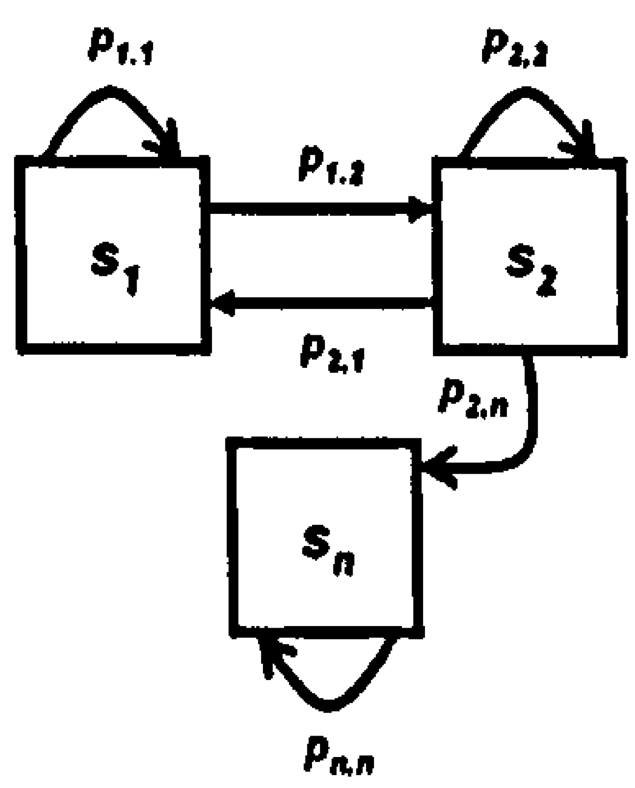

Figure 9: Markov Chain with Absorbing State

If the state s_n is reached via transition $p_{2,n}$, only one transition is then possible. That is $p_{n,n}$ - the probability of remaining in state n. Clearly according to equation 14 $p_{n,n}$ will equal 1, meaning when the system reaches s_n it stays there with certainty. Chains of this kind are well-suited to modelling systems where there is a specific period of operation, often called mission time. An example of this would be a model characterising the deterioration of assets in order to decide when to perform maintenance tasks (See Hoskins et al, 1999). Absorbing states can also be used to good effect within a MCS by re-setting the Markov chain after the absorbing state has been reached. This concept is used in this research and is applied in chapter 4.

The advantages of using Markov chains for modelling of wind turbines are that intermediate states and multiple components can be modelled, as well as failure, maintenance and repair actions. All of these actions and events can be thought of as transitions to different states of the model. These aspects are particularly important in terms of realistic capture of O&M. A further advantage is that because of its state-based nature, condition monitoring can be modelled very intuitively. Since this is a central pillar of the research presented in this thesis, it can be seen that Markov chains exhibit many desirable characteristics.

This section has explained the formulation of a simple Markov chain. As with the classical reliability model, there is more than one method to extract the metrics of interest from such a model. The characteristics and merits of each solution method are now discussed.

3.2.4 Solving a Discrete Time Markov Chain

Markov chains differ from classical reliability models in that they can be used to model a whole process rather than solely failure events. Because of this, there are a number of metrics which can be calculated. The simplest is the time dependent probability, which is the probability of being in a specified state after a particular number of time steps.

The time-dependent state probability is calculated by finding the product of the probabilities of the transitions which lead to the state of interest. A widely-used method do this calculation quickly is the matrix multiplication method, whereby the TPM is multiplied by itself by the number of time steps. As an example, consider the generic system in Figure 8: the probability of being in s_2 after 3 time steps is calculated by taking the matrix in equation 15 and raising it to the power 3, i.e. TPM^3. The new value for $p_{1,2}$ is the probability of being in s_2 after 3 time steps, assuming the starting state was s_1. By applying this technique a large number of times, the steady-state probabilities can also be deduced.

The discrete-time Markov chain solved via matrix multiplication has been successfully applied in many fields. Among the most relevant examples for this thesis is the work of Black, Brint and Hoskins who built on the theoretical foundations but focused their work on real engineering problems. Furthermore, they relaxed some of the underlying assumptions to increase the model flexibility.

Hoskins et al. (1999) aimed to use condition information as an aid to asset management decision-making, using Markov chains to model changes in a plant item's condition over time. The authors produced a homogeneous, discrete-time Markov model to represent circuit breaker condition, which was solved using the matrix multiplication method. Dielectric strength of the oil was used as the condition monitoring (CM) measure, recorded during maintenance and used to populate the model. The time parameter resolution was one year, however no explanation was given regarding the criteria used to discretise the oil condition into states in the Markov model. Possible factors affecting condition as identified in the paper were age, which was considered in the model, and number of circuit breaker operations which was not considered. The authors use two methods to deduce the transition probabilities from the data set: maximum likelihood estimation and method of least squares. However the data had to be in a very specific format for these types of fitting methods to be applied. This data requirement would represent a problem for application of this method to the issues examined in this thesis because datasets comprising many years of asset deterioration records for wind farms are not generally available.

The analysis conducted by Hoskins et al. is used to predict the state of circuit breaker fleet in future years. The analysis is instructive for this research because it shows that a small number of states (in this case, four) is adequate to represent condition deterioration. Although repairs are not modelled in this paper, it is observed that with some modification repair and replacement could be included. This would provide a suitable framework for evaluation of a cyclic system where the equipment is continuously operated and maintained over a shorter time scale, such as wind farms.

Black et al. (2003) proposed use of the semi-Markov method to model deterioration of assets, using oil-filled switchgear and power transformers as two examples. The transition probabilities in the stochastic transitional probability matrix are not constant, rather they are dependent on time spent in the current state and are fitted to a Weibull distribution. This non-homogeneous transition matrix results in a more flexible approach compared with the ordinary Markov chain. The solution for the time-dependent probabilities is obtained by forming analytic expressions (see Appendix A at the end of the thesis for a worked example of this type of solution). Finding analytic expressions for more complex systems where failure and repair are considered is very difficult and for this reason analytic solution is not suitable for application in this thesis.

The authors point out that curve fitting and Markov processes are the two most frequently used methods for predicting future condition, however the rate of deterioration is uncertain and so Markov models fulfil this requirement. They identify several successful implementations of Markov models, citing pavements, bridges, water and electrical networks. An interesting point is the consideration of deterioration itself being of continuous nature: the authors argue that characterisation of the transition probabilities in the semi-Markov model using probability distributions leads to a more accurate representation of the physical processes. A major drawback of this method, however, is the large body of extremely detailed data needed to populate the model. This data requirement is even more onerous than for the previous publication (Hoskins et al., 1999) and is prohibitive to application of this method to WT CM quantification.

Black et al. (2005) compared three methods for modelling asset management problems: Markov, Semi-Markov and time-delay models. The comparison shows that of the three models examined, the semi-Markov method gives the best results. They discussed problems related to modelling condition including the uncertainty of the environment the equipment is exposed to (e.g. weather effects), lack of knowledge concerning past operational history, and lack of suitable data. These data requirements stem from an assumption that only individual sites and the effects of those specific site conditions are of interest. However, it may be the case that a more general analysis of O&M policy is desired, as in this thesis. In that case, the model parameters could be estimated based on expert domain knowledge, high level reliability metrics (such as annual failure rates) or a combination of both, as proposed in this thesis. However in this case it is pointless to apply a semi-Markov model because the data needed to exploit its increased accuracy would not exist.

It can be seen that the Markov chain time-dependent probabilities obtained by matrix multiplication are a good way of evaluating a deteriorating system. This method is particularly well suited to cases of slow deterioration over many years, such as large, static infrastructure items, where the time to failure or time to enter a certain state is desired. There are, however some flaws in this method which limit its applicability.

The primary drawback is that it is difficult to include realistic and multiple operational constraints such as the effect of different maintenance policies and weather constrained operation. Both of these issues are central to wind farm O&M and therefore must be taken account of. Additionally, failures in wind turbines are relatively high in number compared with many other infrastructure items: typically the annual failures are more than one failure per WT per annum (see Table 2). Because of their direct exposure to harsh environments and highly dynamic mechanical loads, wind turbines are relatively unique among power system assets in this respect. In general, WT components, especially rotating elements, deteriorate over a much shorter time period than protected, static items such as circuit breakers. Finally, if the system is cyclical (i.e. the Markov chain is renewed after downtime) but failures are modelled using absorbing states, the system is defined as non-ergodic and steady-state values cannot be calculated based on matrix multiplication. For these reasons, the matrix multiplication method is unsuitable for WT application and other approaches must be considered.

The application of MCS to reliability models was discussed in section 3.2.2. Similar methods can be applied to Markov chains to obtain not only the steady-state probabilities, but also the overall system reliability, and availability when combined with other metrics. A demonstration study is presented in the next section to show the MCS solution of a simple Markov chain.

3.2.5 Simple Monte Carlo Study

The main difference between using MCS to solve a binary reliability model and a Markov chain is that often there may be more than two possible outcomes of a trial, as was illustrated in Table 6. This means that more than one comparison may be necessary. Taking the non-ergodic system in Figure 9 as an example, if the system is in s_2 then there are three possible transitions ($p_{2,1}$ $p_{2,2}$ $p_{2,n}$). Table 8 shows a TPM for the non-ergodic system, with the absorbing state clearly identified as having probability of unity of staying in the state once it is reached ($p_{n,n}$=1).

From/To	s_1	s_2	s_n	Sum
s_1	0.8	0.2	0	1
s_2	0.1	0.8	0.1	1
s_n	0	0	1	1

Table 8: Transition Probability Matrix for Basic Non-Ergodic System

Since the rows of the Markov TPM sum to 1, this can be thought of as a cumulative distribution of the transition probabilities: this is visualised for the case of s_2 in Figure 10. MCS is applied to this system by comparing the generated PRN, which is uniform between 0 and 1 (see equations 11 and 12), with the thresholds shown explicitly in Table 9.

MCS Condition in s_2	Transition
$0.1 \succ PRN_t \succ 0$	Move to s_1
$(0.1+0.8) \succ PRN_t \succ 0.1$	Stay in s_2
$(0.1+0.8+0.1) \succ PRN_t \succ (0.8+0.1)$	Move to s_n

Table 9: Monte Carlo Simulation of Markov Chain when residing in s_2

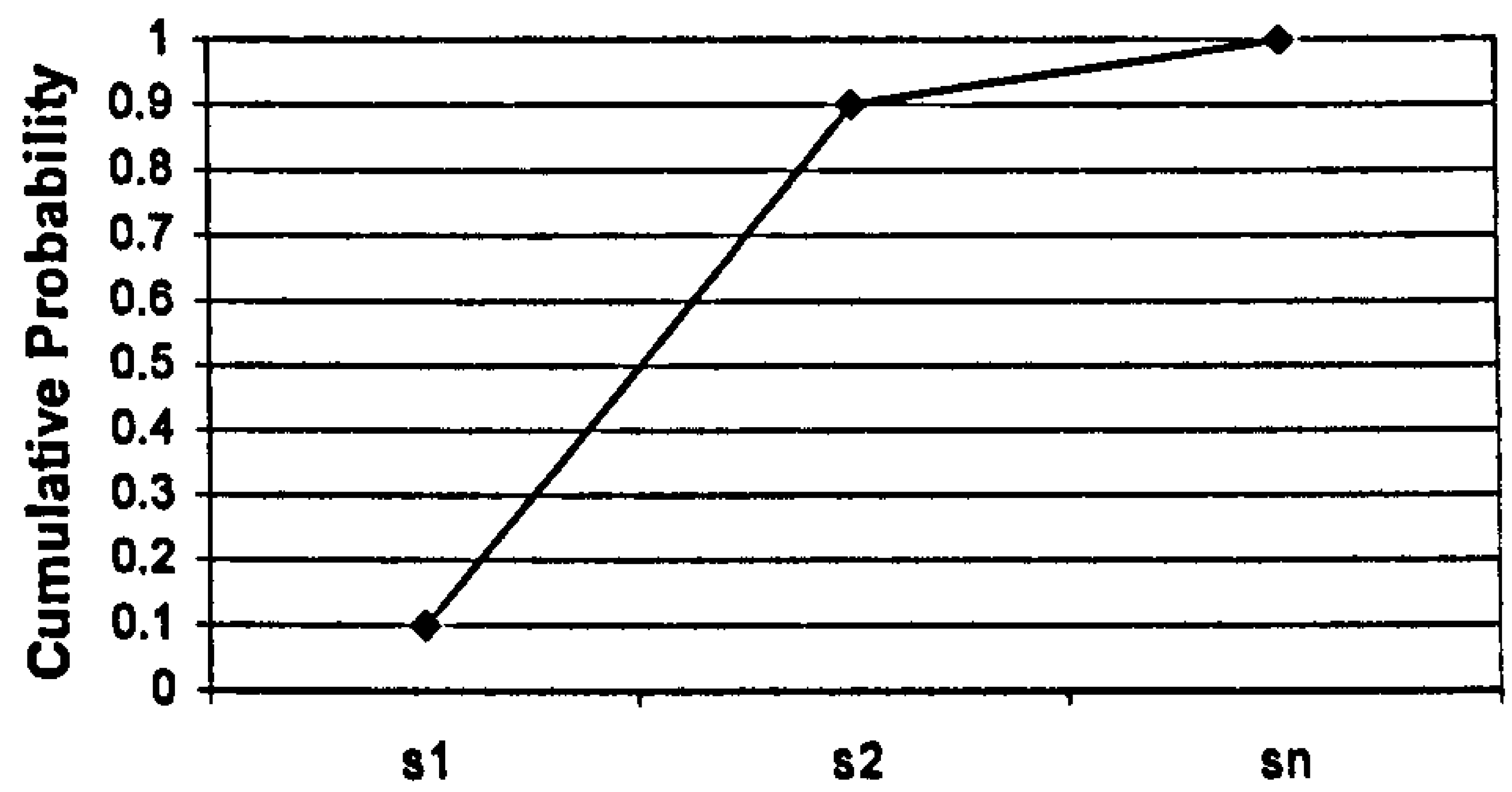

Figure 10: Cumulative Distribution of s_2 Probability Transitions

Instead of calculating if the system is simply 'operational' or 'failed' at each trial, as in the case of the classic reliability model, or calculating the probability of being in each state, as in the matrix multiplication method, the Markov model simulates a condition trajectory of the system as if it were actually in operation. Intuitively this is easy to appreciate, since it is analogous to the real process. 20 trials of the process are simulated in Table 10, based on the same PRN sequence previously used.

In order to calculate the steady state values of the Markov chain, the frequency of occurrence of each state (fs_1, fs_2 and fs_n) relative to all the other system states must be determined over the duration of the 20 MCS trials.

Trial	PRN	Pre-Trial State	Post-Trial State	Trial	PRN	Pre-Trial State	Post-Trial State
1	0.820	1	2	11	0.773	2	2
2	0.152	2	2	12	0.315	2	2
3	0.172	2	2	13	0.795	2	2
4	0.526	2	2	14	0.916	2	N
5	0.003	2	1	15	0.506	N	N
6	0.123	1	1	16	0.258	N	N
7	0.357	1	1	17	0.399	N	N
8	0.972	1	2	18	0.884	N	N
9	0.222	2	2	19	0.575	N	N
10	0.160	2	2	20	0.246	N	N

Table 10: Monte Carlo Simulation of Non-Ergodic Markov Chain

Based on the proportions of these state frequencies, the steady-state probabilities for each state (Ps_1, Ps_2 and Ps_3) are calculated. Equation 16 shows an example of this calculation for Ps_1.

$$P_{s_1} = \frac{\sum_{trials=1}^{20} f s_1}{\sum_{trials=1}^{20} f s_1 + \sum_{trials=1}^{20} f s_2 + \sum_{trials=1}^{20} f s_n} \tag{16}$$

From Table 10 it can be calculated that the frequencies fs_1, fs_2 and fs_n are 3, 10 and 7 respectively. Therefore applying equation 16 for Ps_1:

$$P_{s_1} = \frac{3}{3+10+7} = \frac{3}{20} = 0.15$$

Similar calculations can be carried out for states 2 and n, so that Ps_1=0.15, Ps_2=0.5 and Ps_n=0.35. How these steady-state probabilities are then used depends on the system being analysed and the metrics of interest.

One engineering metric of interest in this thesis is the availability of the modelled system: that is the time that the system is operational relative to the total time period considered. For the non-ergodic system considered here (refer to Figure 9), if the states s_1 and s_2 were modelled as 'operating' states and s_n was modelled a 'failed' state, then the availability of the system could be calculated based on these definitions. Equation 17 shows the calculation for availability, which is a function of the steady-state probabilities previously calculated (Ps_1, Ps_2 and Ps_3). For this particular example, the availability of the system is 0.65, or 65%.

$$A = \frac{P_{s_1} + P_{s_2}}{P_{s_1} + P_{s_2} + P_{s_n}} \tag{17}$$

$$A = \frac{0.15+0.5}{0.15+0.5+0.35} = 0.65$$

Further advantages of using MCS to solve the Markov chain are that repair can be modelled in different ways (either as a transition probability, or as an absorbing state which is restored to operation after deterministic downtime or probabilistic downtime duration), and that constraints are very easily modelled. This key feature is expanded on later in the thesis.

Markov chains by implication are discrete-time, however a discrete time parameter is not always desirable or suitable for all problems. Therefore the next section explains how the ideas of Markov are extended to continuous-time problems, which are much more abundant in the literature on deterioration, maintenance and failure modelling.

3.2.6 Markov Process

The Markov chain described previously is based on the assumption that time is split up into discrete, equal steps, for which the TPM is defined. Intuitively this is a simplification of the real process, since deterioration, failure and repair are continuous-time processes. Therefore the Markov process, although based on the same assumption of constant failure rate, is defined differently to the discrete-time case. What is of particular interest in the context of this thesis, is what extra functionality, detail or drawbacks there are relative to the Markov chain.

Instead of transition probabilities governing the behaviour of the system, transition rates are adopted. They are associated with the exponential distribution introduced in the classic reliability model, since constant failure rates are assumed. The transitions are expressed in terms of deterioration rates ($\lambda_{1,1}$, $\lambda_{1,2}$ etc.) and repair rates ($\mu_{2,1}$) – see Figure 11 for an example of the continuous-time case of the non-ergodic system considered earlier. Although a discrete time period is not specified, clearly the period of time considered must be the same for all the transition rates in the Markov process.

Indeed, it is possible to derive a TPM for the continuous process (equation 18 for the case of Figure 11) by introducing a time step Δt where the transition probability is $\lambda\Delta t$. To put this another way, if the transition rate for a given time step is known, the transition probability for any other time step can be calculated proportional to the size of the new time step, providing that the probability of more than one event occurring during Δt is negligible. As with the discrete time case, all rows of the discretised continuous-time TPM sum to 1.

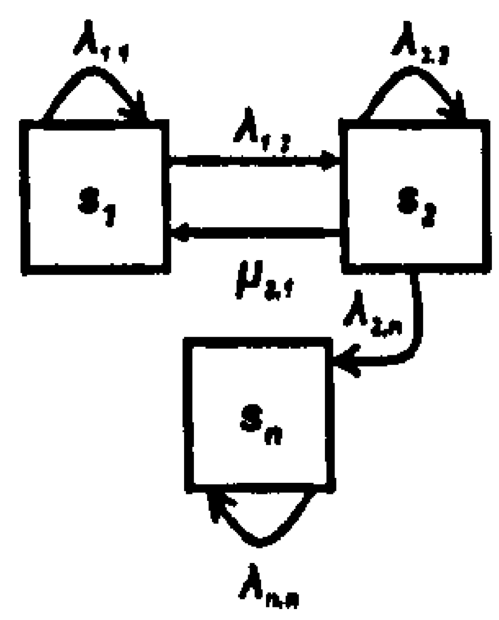

Figure 11: Markov Process

$$TPM = \begin{bmatrix} 1-(\lambda_{1,2}\Delta t) & \lambda_{1,2}\Delta t & 0 \\ \mu_{2,1}\Delta t & 1-(\mu_{2,1}\Delta t+\lambda_{2,n}\Delta t) & \lambda_{2,n}\Delta t \\ 0 & 0 & 1 \end{bmatrix} \tag{18}$$

3.2.7 Solving a Continuous Time Markov Process

Obtaining the solution of a Markov process can be achieved in several ways. The matrix multiplication method and MCS can both be applied in largely the same way as for the discrete time case (Markov chain). However, the most widely adopted method for solving a Markov process is to find the analytical solution to the simultaneous equations which arise based on the process.

The non-ergodic system in Figure 11 is simplified in order to demonstrate the analytic approach. The changes are as follows: there are no repair rates (μ) and all transition rates are equal ($\lambda_{1,2}= \lambda_{2,n}= \lambda$) – the resultant system is shown in Figure 12. If the single time step Δt is considered so that the probability of simultaneous events is negligible, then the probabilities of being in each state after Δt has elapsed are expressed by equation 19, equation 20 and equation 21.

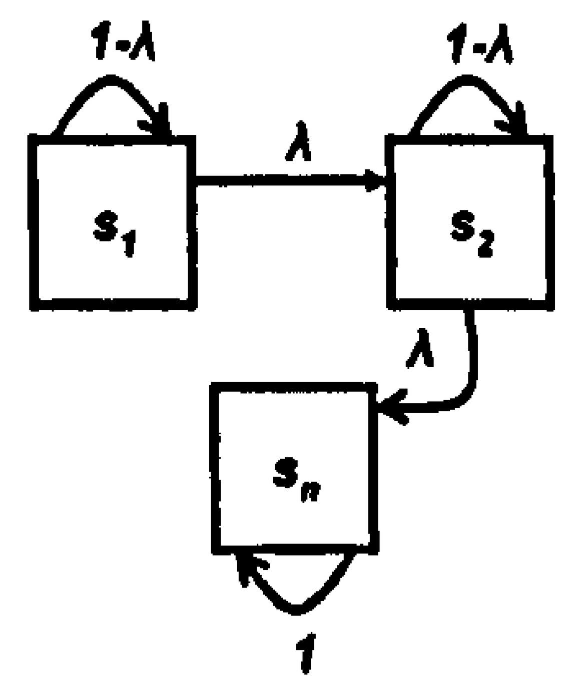

Figure 12: Simplified Markov Process

$$P_{s_1}(t+\Delta t) = (1-\lambda\Delta t)\, P_{s_1}(t) \tag{19}$$

$$P_{s_2}(t+\Delta t) = (1-\lambda\Delta t)\, P_{s_2}(t) + \lambda\, P_{s_1}\Delta t \tag{20}$$

$$P_{s_n}(t+\Delta t) = P_{s_2}(t)\, \lambda\Delta t + P_{s_n}(t)\,(1) \tag{21}$$

Taking equation 19 as an example, the probability $P_{s1}(t+\Delta t)$ of being in s_1 after time step Δt is calculated by multiplying the probability of being in s_1 at time t, $P_{s1}(t)$, by the probability of staying in the same state after one time step $(1-\lambda\Delta t)$. Equation 20 and equation 21 were derived in exactly the same way. Appendix A shows how the expressions can be manipulated into matrix form, for which the final expression is equation 22.

$$\begin{bmatrix} P'_{s_1}(t) & P'_{s_2}(t) & P'_{s_n}(t) \end{bmatrix} = \begin{bmatrix} -\lambda & \lambda & 0 \\ 0 & -\lambda & \lambda \\ 0 & 0 & 0 \end{bmatrix} \times \begin{bmatrix} P_{s_1}(t) & P_{s_2}(t) & P_{s_n}(t) \end{bmatrix} \tag{22}$$

Appendix A also shows how the expression for reliability and mean time to failure of the system can be derived by manipulation of these equations. The expressions for reliability and MTTF are expressed in equation 23 and equation 24 respectively.

$$R(t) = P_{s_1}(t) + P_{s_2}(t) = (1+\lambda t)\, e^{-\lambda t} \tag{23}$$

$$MTTF = \frac{2}{\lambda} \tag{24}$$

The numerical values are calculated by substituting the values for λ and t into these equations (sometimes called direct methods). The simplified expression of reliability in equation 8 can be substituted into equation 23 and yields very similar results, as illustrated in Table 11. It can be concluded that, as in the case of the classic reliability model, the use of 'approximate' $1-\lambda t$ rather than 'exact' $e^{-\lambda t}$ is adequate for evaluation of a Markov process. This is illustrated by the fact that if $\lambda=0.01$, then the approximate reliability expression, $1-(\lambda t)^2$, matches the exact expression, $(1+\lambda t)e^{-\lambda t}$, to four decimal places.

λ	t	$R(t)=(1+\lambda t)e^{-\lambda t}$	$R(t)=1-(\lambda t)^2$	# decimal places accuracy
0.1	1	0.99532	0.99000	2
0.01	1	0.99995	0.99990	4

Table 11: Accuracy of Full and Approximate Expressions of Markov Process System Reliability

Direct solution, as Appendix A illustrates, is an extremely tedious and potentially error-prone way of solving a Markov chain, even for very simple cases of only three states and equal transition rates. When more states or more transitions such as repair are introduced, the degree of difficulty to get the solution increases significantly.

Alternatively, numerical methods such as Newton-Raphson can be used to solve the simultaneous differential equations which arise from equation 22 or equivalent. The main advantage of this type of solution is its iterative nature, and resultant suitability of implementation using a programming language. Numerical techniques are therefore often used instead of direct methods to obtain the analytical solution.

The key exponents of the Markov process in the power systems domain are Anders, Endrenyi and colleagues. Their work focuses on applications to various generation, transmission and distribution assets and is therefore of high relevance to this thesis. Their preferred method of solution is analytic, the early work deriving the expressions directly.

Anders et al. (1990) presented a probabilistic model to estimate the remaining life of generator insulation. This paper is relevant to this thesis because it demonstrates the applicability of Markov chains to power generation asset modelling. The author described site-specific factors affecting the frequency and deterioration of the insulation such as temperature, voltage, materials, maintenance and random events, and processes such as thermal ageing and abrasion were identified. The authors proposed two main methods of measuring such processes: monitoring relevant signals via instrumentation (i.e. CM) and effects observable via inspection. The paper includes an interesting section describing the discrete- and continuous-time versions of the model, as well as a small section on parameter estimation from available data.

The authors point out that uncertainty in the model can be reduced by taking measurements from equipment with similar characteristics. For example, in a WT application, the reliability of blades is likely to be the similar for all 2MW 3-bladed Danish concept WTs (i.e. shared rating and design configuration). The same is suggested for operating conditions, i.e. equipment operating under similar conditions (atmospheric, environmental) could be used to characterise a general model for that kind of operating condition. Finally the authors say that the two main challenges for future research are the adequate definition of states to represent the deterioration, and definition of the transition probabilities as the desired data may not exist.

Endrenyi et al. (1998) present an analytical software tool linking maintenance effects to reliability component ageing. The authors describe the maintenance-reliability-economy tradeoff for which the program identifies the most suitable maintenance policies.

The Markov model developed by the authors represents three levels of deterioration and a failure state for a single electrical plant item, presumably represented by a single parameter, although no information was given on what constituted the condition measure. Minor and major maintenance were considered as separate states in the model – as well as a probability of a single-step condition improvement the model also included probability of the maintenance having no effect and negative effect. This represents a refined representation of the effects of maintenance, however this level of detail is not considered in this thesis. The reason for this is that it is pointless to include sophisticated maintenance models without either data or expert opinion to form an estimate of the frequency of occurrence of these unsuccessful maintenance events, and neither were available for the duration of this research. Finally, a CBM policy was considered via a simplified model, and for both models a sensitivity study was conducted to yield the optimal maintenance policy. This is a useful approach as it allows the robustness of the solution obtained by the model to be tested. Sensitivity studies are used in a similar fashion later in this thesis.

Endrenyi et al. (2004) compared two methods of evaluating effects of maintenance on both reliability and operating costs. These two methods were Reliability-Centred Asset Manager (RCAM) and Asset Sustainable Strategy Platform (ASSP) as used by Swedish and Canadian utilities respectively. Both methods use reliability analyses to rank the most influential system components and examine the impact of maintenance on the failure rates. This approach necessitates a very deep analysis of time-varying failure rates which is beyond the scope of this thesis. For the WT CM evaluation application considered here, maintenance is considered as restoring the equipment to 'as good as new' state.

RCAM establishes the relationship between maintenance policy, cause of failure and time. The revised component reliability is used to compute the new overall system reliability. ASSP uses a Markov model for deterioration and maintenance effects, the effectiveness of which is measured via mean time to first failure. Through successive iterations the maintenance policy is optimised. Some fundamental questions were posed, such as quantification of maintenance costs, and how maintenance is defined (e.g. manufacturers' specification, experience etc.). For the purposes of this thesis, time-based maintenance is considered to be conducted twice per annum onshore and once per annum offshore, as dictated by current wind industry practice.

Analytic methods are widely applied in the literature. Anders, Endrenyi and associates adopt analytic solution in all the referenced papers – see Anders et al. (1990), Endrenyi et al. (1998) and Endrenyi et al. (2004). This is perhaps due to their perceived mathematical rigour and greater elegance, a fundamental drawback of analytic methods is the difficulty in building in model constraints for specific operating conditions. Since it is expected that a model of wind turbine O&M will include such constraints, analytic solution is not a feasible option. Research which has successfully included such constraints often reverts to MCS as the solution method, and the same approach is taken in this thesis.

Researchers at the polytechnic university of Milan proposed an alternative approach to the previously adopted methodology of Markov models solved via analytic solution. Their main innovation was use of Monte Carlo simulation to find the solution of a Markov chain as opposed to direct or numerical solution.

A continuously monitored multi-component system is considered by Barrata et al. (2002), which deteriorates according to a discrete-time Markov chain and is solved via Monte Carlo simulation. The main advantage of this approach is that it can cope with the dimensionality of problems when several multi-state components make up the system, in contrast to analytic methods. The authors take an interesting approach to repair processes: the repair times follow a lognormal distribution which is dependent on the level of recovery the component achieves. When this time has elapsed, the repair is carried out with certainty (probability=1): this can be thought of as a combination of discrete Markov chain and time delay model. The cost-optimisation of the model is done via a simple sensitivity study. It is noted, however, that the large number of proposed states for the component deterioration (~30) is impractical from a parameter estimation viewpoint. Similarly, it is doubtful whether enough data exists to derive probabilistic models of downtime duration for a WT application. It may be possible in applications with more established regimes for data collection, e.g. the aviation industry.

Marseguerra et al. (2002) identified two main issues for modelling the implementation of a condition-based maintenance (CBM) strategy in the nuclear safety domain: a predictive model describing the future deterioration of the system in question, and an evaluation/ optimization of the possible maintenance strategies. Use was made of a Markov Chain solved by Monte Carlo sequential simulation to characterise deterioration of a single component. The model simulates the physical process and attempts to maximize revenue and equipment availability by using a genetic algorithm to establish the maintenance threshold level. The model assumes a steady deterioration process, but also includes a probability of outright 'shock' failure which is assumed to be a linear function of the deterioration level. The authors illustrate that the number of states used to characterize the deterioration process is an important consideration, with a larger number of states increasing the accuracy of the result. However, the number of states mentioned (71) and the fact that no mention is made of the data source used suggests that the modelling framework is the focus of the research rather than a real application. That is in contrast to this thesis, and for this reason such huge numbers of states are considered highly impractical from the viewpoint of data and parameter estimation.

Zio & Podofillini (2007) explored the spares allocation problem. They explain that holding spares, while necessary for safety-critical systems, is very costly and often components are never used. MCS is used to model failures and spares, although intermediate deterioration is not considered. Apparently ad-hoc rules are applied to the transition probabilities in order to replicate real-life behaviour: in one case the transition probability is increased by orders of magnitude to ensure an immediate transition to the operational state after a spare has been installed. While never calling their model a Markov chain, the model strongly resembles one and is rather vaguely called a 'Markov-type model', perhaps because of the relaxation of some Markov properties i.e. stationarity, memory etc. Finally the authors discount more established methods of optimisation ('gradient methods' i.e. numerical iteration, dynamic, integer, mixed integer and non-linear programming) because too many simplifications are needed and they need very detailed answers since safety is a primary consideration of their work on nuclear power plants.

The use of a Markov chain or process combined with MCS represents a good enabler between use of Markov models as a process model and modelling accuracy in terms of constraints and maintenance events. Intuitively, and on the basis of Appendix A, it is clear that a large multi-state model will be very difficult to formulate. Such a case is likely for modelling of wind turbine deterioration, failure and operations: especially since multiple components need to be modelled. Therefore analytic methods are not suitable for this problem.

3.2.8 Miscellaneous Approaches to Asset Modelling

The different forms of classical reliability models and Markov models are the most prevalent in the literature and also fairly easy to categorise, however other methods have been applied. The most prominent of these is the time delay model (TDM) of Christer and colleagues. Rather than using probability distributions to model the failure rate or reliability function, the arrival time of the event is characterised.

Baker and Christer (1994) charted the development of the 'delay-time' model, usually characterised by a homogeneous Poisson process (HPP). The authors are critical of contributions which neglect parameter estimation, model validation or lack of applications to real systems. The authors point out that there is very little point in developing complex theoretical models if data does not exist to estimate multiple parameters. On the other hand, they do suggest that subjective information could be used where data are scarce. The two stage delay-time model was described: essentially this is analogous to a three stage Markov deterioration model. The paper argues that pragmatic decision rules should be adopted, since these have more chance of being adopted in real situations. For some complex systems, all failures are pooled into one model, and various assumptions can be made depending on which aspects of the problem are crucial. The authors continually emphasise the philosophy that 'no purely theoretical model can be expected to cope with all details of practice'. Practical experience indicted that a few hundred samples of faults are sufficient to represent the systems adequately and to form cost-effective policies via modelling.

Other research into asset modelling exists which does not fall under the headings previously discussed and provides useful contextual information: however none of the methodologies meet the requirements of the modelling task as fully as the Markov model coupled with MCS.

Archibald et al. (2004) considered the sensitivity of a pre-defined optimal maintenance strategy to changes in the model parameters, focusing mainly on financial aspects such as discount rate and cost of maintenance and replacement. The authors employed a non-homogeneous Poisson process as the failure model, applied to a large water filtration system.

Their results showed that the model was most sensitive to cost of preventive maintenance and repair cost after failure. The idea of testing how the results of asset modelling could change with respect to variables of interest, not limited to cost, is a very useful one and will be used in this thesis. Cost of maintenance and replacement, as in the work of Archibald and colleagues, is of interest as well as technical variables such as component reliability. The authors concluded their work by pointing out that more attention needed to be given to the nature of maintenance over a long period of time as the equipment ages and completes a large number of duty cycles. This aspect is one the wind industry will be keen to address in the future as large numbers of wind farms enter the end of their life cycle, but as yet this is not a particularly pressing problem owing to the relative immaturity of the wind industry.

The aim of Ansell et al. (2003) was to lower costs for a water infrastructure utility by understanding the underlying failure processes of the equipment. They did this by using a data driven approach which did not assume any underlying distribution for the failure rate evolution over time. A method called Cox regression was used which enables equipment condition rating to be included in the regression lifetime. This enables an instantaneous failure rate at various points in time to be calculated, however the time in between is set to zero failure rate, therefore 'smoothing' techniques are used to 'spread' the failure rate over time. Thus a time-dependent failure characteristic was produced, which would not have fitted any assumed prior distribution. Averaged costs were used for maintenance and refurbishment events because of a lack of information. Data seemed to be a problem for the authors since they had only 4 years of operational data for an asset whose life was ~40 years. They overcame the data scarcity by fitting a model to the early life stage and then using this every time a refurbishment occurred. Using this technique they estimated the impact of refurbishment compared to increased maintenance costs enabling more informed decision-making. Even in the case of this pragmatic approach, a great deal of data was needed: this seemed mainly to be because of the very long equipment life of the asset.

Thomas (1996) considered some fundamental questions regarding representation of condition in deterioration models and gave an overview of influential work in the area. Suggested areas identified for application of improved maintenance via deterioration modelling were: bridges, railways, pipelines and electrical pylons. Particular focus was placed on the successful implementation of Markov models to the management and maintenance of the United States highway and pavement systems.

The author specified three points of importance when building up a deterioration model, these were: inspection, classification and decision-making. Inspection focused on how the data are to be obtained, classification on how the condition is to be expressed or quantified, and decision-making on what actions could be taken to optimise the behaviour of the system. Three distinct methods of classifying condition were identified by the author: subjective index, overall index comprising weighted terms of many variables, and multi-dimensioned description. The last of these three seems most applicable for modern on-line condition monitoring. Finally, several methods were introduced for optimisation of the maintenance process: linear programming, Markov decision process, expert systems, and random search techniques.

Billinton and Li (2004) illustrated a probabilistic model for power generating units which went beyond the conventional up/ down model. Instead of the well-known forced outage rate (FOR), often used in reliability studies to derive the generator failure rate, the study used derating-adjusted forced outage rates (DAFOR). A method known as the apportioning method was used to derive three and four-state generator models instead of the usual two-state model. The apportioning method 'absorbs' contributions to its probability on the basis of the distance from the 'real' derated levels, thus creating a discretised multi-state generation model. These intermediate derated states, in which the unit operated at a proportion of its full rated output, provide a more complete view of the generation unit operation. The authors illustrate this through application of their model, which shows that conventional studies based on simple two-state representation may be conservative due to their lack of consideration of these derated levels, which are often prevalent in real systems.

3.2.9 Summary of Asset Modelling Methods

The following conclusions are reached after considering the various modelling options available for modelling deterioration, failure, operation and maintenance of wind turbines within a wind farm.

- Models and studies representing deterioration and maintenance processes are very well established in literature, with applications both numerous and varied. Markov models in various forms are the favoured modelling framework.

- Markov models, through their state-based nature, allow the key aspects of the condition deterioration process and CM to be captured. They also have the flexibility to interface with other models, the physical Markov model typically being interfaced with an economic or functional model.

- By using MCS to solve the Markov model, the solution can be obtained even if the system is highly complex. Through the use of statistical tools, the level of accuracy in the results can be as high as required in the simulation time available.

These factors were taken into account when identifying a suitable methodology to move forward with the modelling of wind farm processes, with a view to quantifying the benefit of condition monitoring. Figure 13 shows the decision making process, influenced by points noted in the literature review.

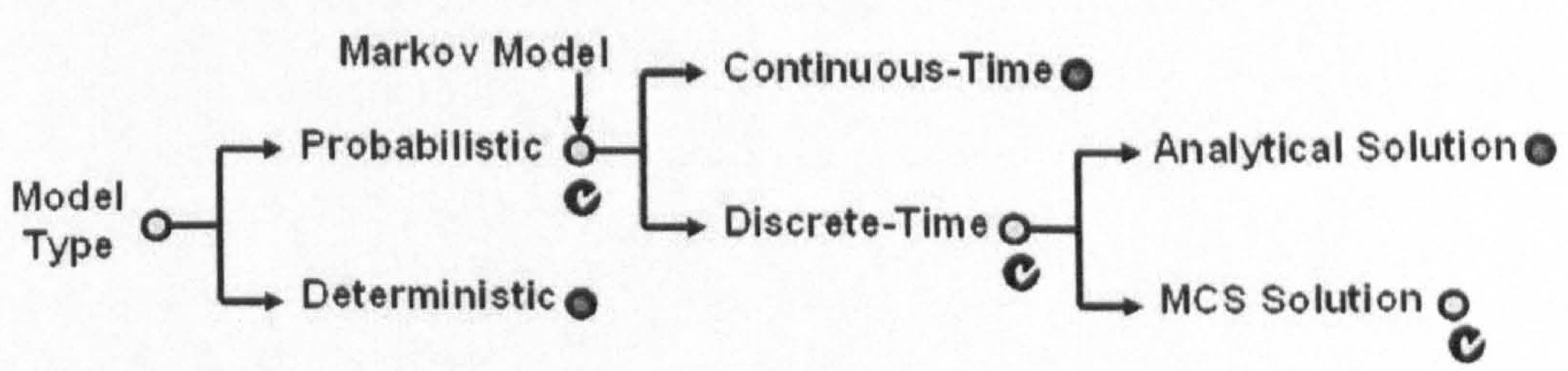

Figure 13: Asset Modelling Decision Process

Thus, the Markov Chain solved via Monte Carlo simulation was identified as the most suitable approach for the work contained in this thesis. The chief motivations for this choice are:

- High degree of modelling flexibility
- Less constrained than continuous-time models re: multi-component complexity
- Easily able to accommodate new features e.g. operational modelling
- Can be easily tailored for different systems re: number of states and components
- Ease of interface with other layers of modelling
- Time-dependence can be achieved with a multi-stage model

The Markov model represents the physical WT component condition, and is able to include CM information. Other aspects of the WT performance, such as energy yield, wind regime, economics, operations and maintenance policy also have to be considered. The next section explains the modelling approach including these aspects.

3.3 Wind Speed Characterisation & Energy Yield Model

Simulation of wind turbine operational practice necessitates adequate representation of wind speed. The reason for this is that maintenance actions and access to site are coupled with wind speed directly, and also energy yield is based on the wind model coupled with a WT power curve. In the case of this thesis a deep understanding of the mechanics of wind direction and interaction with structures is not required. Rather the key requirements of the wind speed model are:

1. Maintain sufficient accuracy (c.f. the real profile)
2. Construct in a form which is easily simulated
3. A realistic number of parameters, in view of available data

A literature review of models used for characterisation of wind speed was conducted, with the results summarised in Table 12. Since the AR model can capture the wind speed characteristics adequately and the parameters are easily estimated, this method was adopted for the analysis in this thesis.

Acronym	Description	Advantages	Limitations
AR	Auto-regressive	Well-established heuristic for model classification, good understanding of physical process.	Low accuracy if applied to non-stationary data
MA	Moving average	Appropriate for non-stationary data	Possible un-necessary complexity
ANN	Neural network	Complex multi-variate inter-dependencies can be captured.	Lack of understanding of coupling mechanism. High data requirements.
MC	Discrete State Markov chain	Intuitive state-based modelling framework	Lost detail in state-based representation.

Table 12: Possible types of wind speed model and their characteristics

$$z_t - \mu = \phi_1(z_{t-1} - \mu) + \phi_2(z_{t-2} - \mu) .. + \phi_p(z_{t-p} - \mu) + a_t \qquad (25)$$

The generalised autoregressive process is shown in equation 25 (Box & Jenkins, 1970 p9). It is based on deviation from the mean of the process (z_t-μ), which is calculated as a sum of previous deviation values in the time series (z_{t-1}-μ, z_{t-2}-μ, ... z_{t-p}-μ). These previous deviation values are each weighted according to their influence ($\varnothing_1, \varnothing_2 ... \varnothing_{t,p}$). The system is also subject to random shocks which are normally distributed (a_t) with zero mean. After the AR framework has been adopted, there are two further tasks to successfully implement a wind speed model. The first of these is commonly referred to as model classification, in this case meaning the number of auto-regressive parameters to be included. The second issue is parameter estimation, which is discussed in the next chapter.

3.3.1 Model Classification

The model classification problem for the AR model can be put in lay-mans terms by observing how far back in the past the modeller has to look in order to accurately characterise the wind speed. There is no formal procedure for model classification: indeed, consultation with mathematical experts throughout the duration of this research has merely confirmed this fact. However, some heuristic-based methods are available and have been used for similar problems. The rules involve inspection of the auto-correlation and partial auto-correlation functions. The autocorrelation function (ACF) is a measure of how well correlated a time series is with itself at k time steps (lags) in the past. One component of the ACF is the autocovariance, γ. At lag k it can be defined in terms of deviations from the mean of the series μ_z at time t and at lag k (Box & Jenkins 1970 pp27-28): this is shown in equation 26. The ACF at lag k, ρ_k, is related to the autocovariance and the variance of the series, expressed in equation 27.

$$\gamma_k = \frac{1}{N}\sum_{t=1}^{N-k}(z_t - \mu_z)(z_{t-k} - \mu_z) \tag{26}$$

$$\rho_k = \frac{\gamma_k}{\sigma_z^2} \tag{27}$$

Therefore, in order to calculate the ACF for a wind speed time series, autocovariance (γ), variance (σ_z^2) and mean (μ_z) must be estimated from wind speed data. The mean and variance are well-known quantities and are estimated using equation 28 and equation 29 respectively (Box & Jenkins 1970 p38).

$$\mu_z = \frac{1}{N}\sum_{t=1}^{N} z_t \tag{28}$$

$$\sigma_z^2 = \frac{1}{N}\sum_{t=1}^{N}\left(z_t - \mu_z\right)^2 \tag{29}$$

Using equation 27, the ACF can be calculated from wind speed data for different lags. The algorithm was initially coded in an excel spreadsheet in order to gain a good understanding of its mechanism. Figure 14 is a plot from this spreadsheet, and is based on 10 minute interval SCADA data from a utility wind farm, which has been averaged to 1 hour intervals. The main purpose is to illustrate the influence of time resolution: there is significant coupling at high lag values and many, many model parameters would need to be estimated in the case of Figure 14. In order to simplify the plotting of ACF, the statistical programming language, R, was adopted: this has the useful feature of instantly plotting the ACF without having to re-calculate in the spreadsheet model.

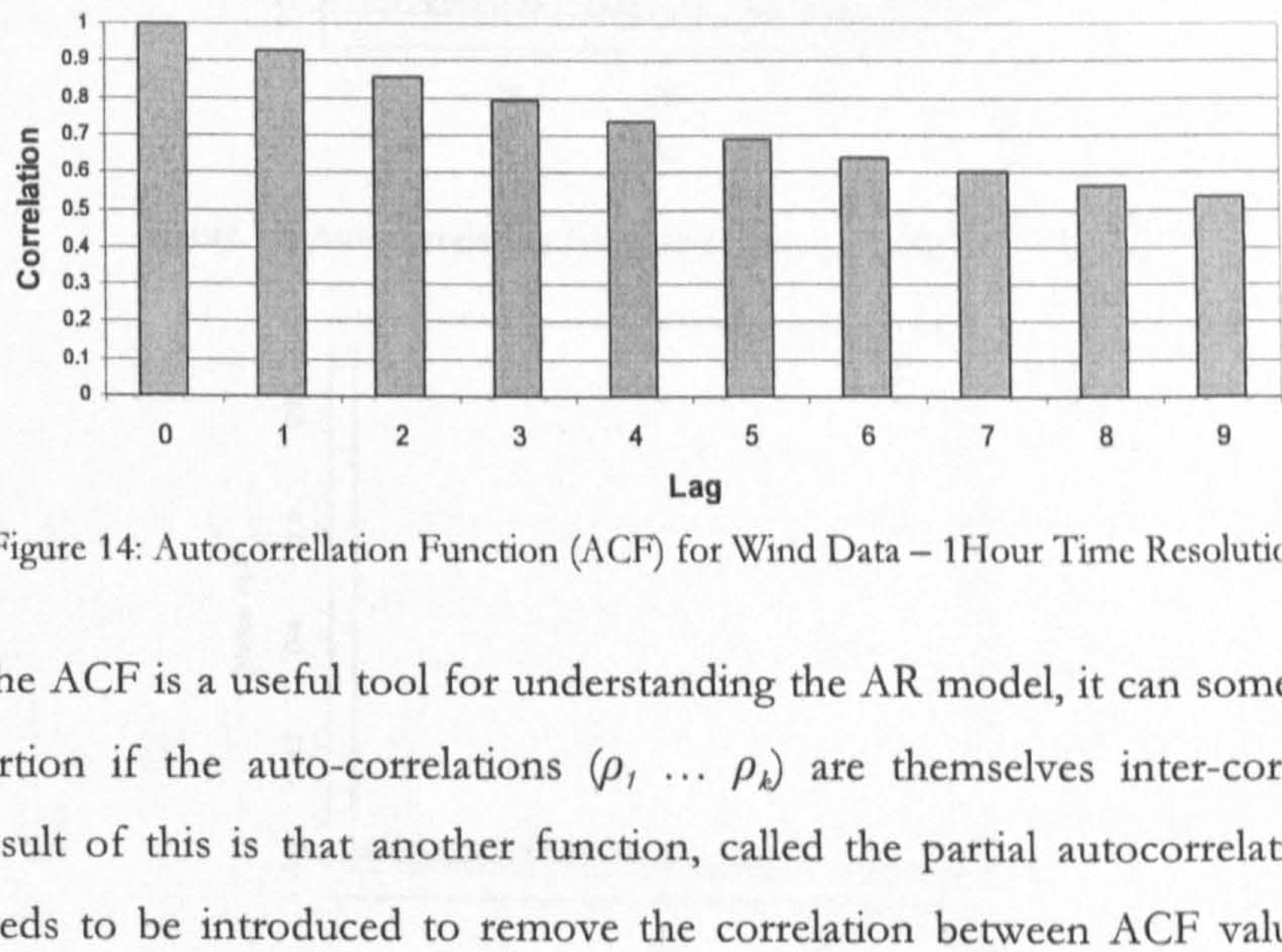

Figure 14: Autocorrellation Function (ACF) for Wind Data – 1Hour Time Resolution

Although the ACF is a useful tool for understanding the AR model, it can sometimes suffer from distortion if the auto-correlations (ρ_1 ... ρ_k) are themselves inter-correlated. The practical result of this is that another function, called the partial autocorrelation function (PACF) needs to be introduced to remove the correlation between ACF values, enabling model classification. The PACF coefficients of interest can be found by solving for ϕ_{kk}: (that is the last coefficient) in equation 30, where ρ_k is the autocorrelation of the series at lag k and ρ_{k-i} is the autocorrelation at various time steps, i, from lag k.

$$\rho_k = \sum_{i=1}^{k} \phi_{ki}\rho_{k-i} \tag{30}$$

It is therefore ϕ_{kk} which is plotted at various lag values which constitutes the PACF. Figure 15 and Figure 16 show both ACF and PACF for wind speed data of 1 hour resolution. The dotted line displayed on these plots represent a single plus and minus standard deviation (refer to equation 29) of the ACF or PACF coefficients. The lines are used as a guide to understand the significance of the correlation. A significant correlation value would be larger than the single standard deviation line.

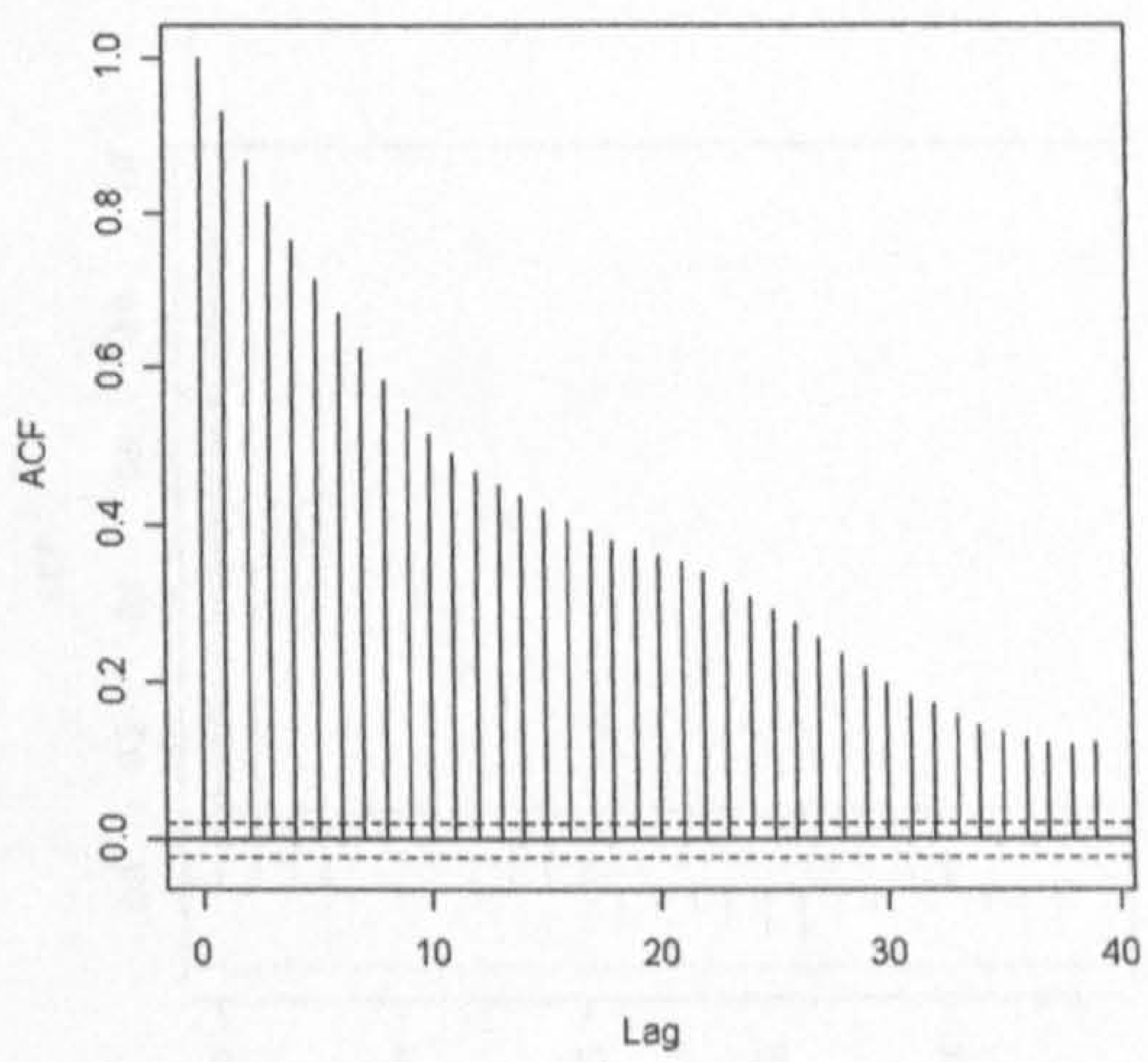

Figure 15: Autocorrelation function at time resolution of 1 hour

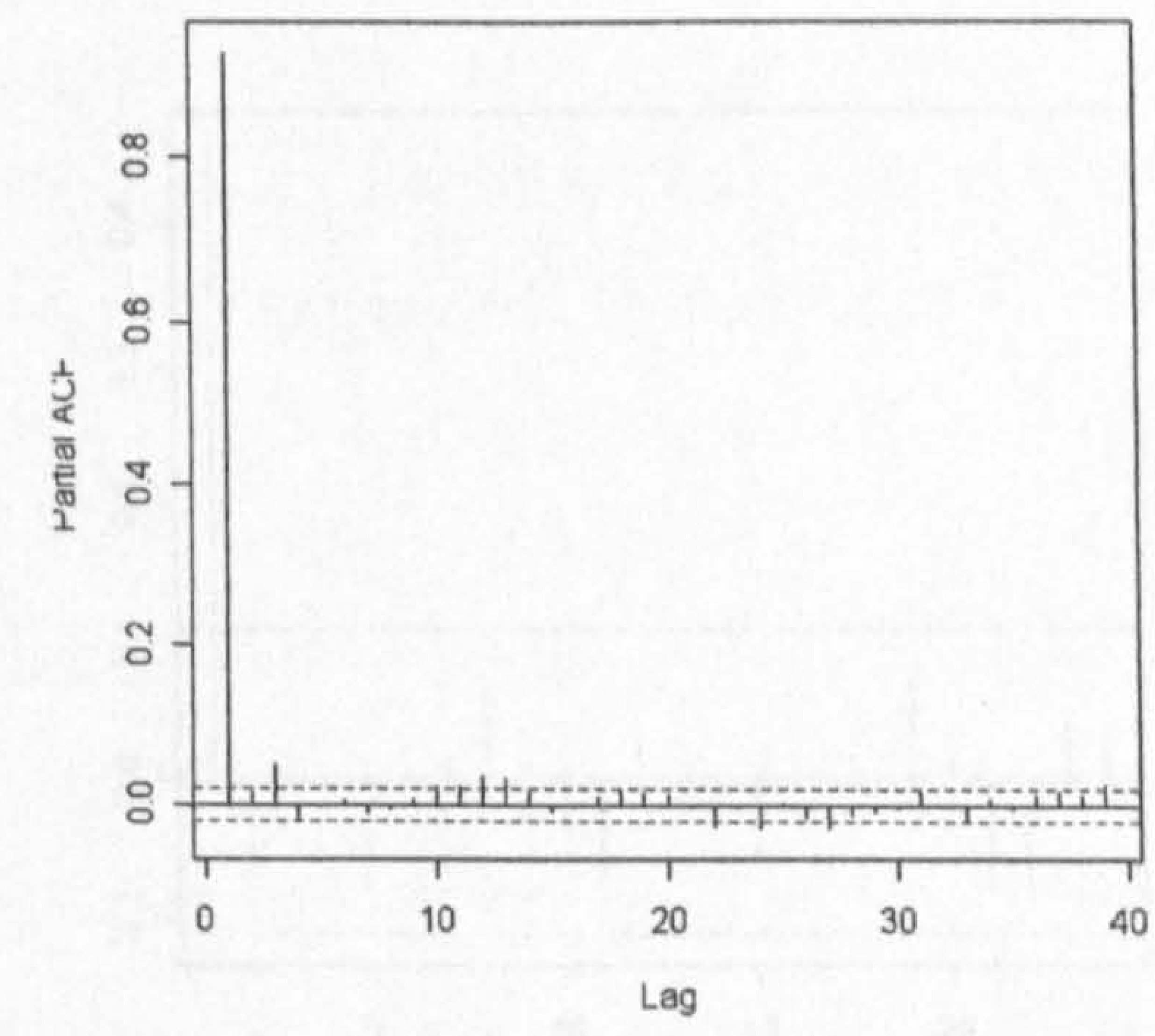

Figure 16: Partial Autocorrelation function at time resolution of 1 hour

Figure 15 and Figure 16 are plotted up to a lag of k-40. It can be observed in the ACF that coupling is significant at high lag values. Even at lag 40 the ACF is much larger that one standard deviation, but this does not necessarily mean that 40 AR parameters would be required to adequately model the wind speed at this hourly resolution. However, since the wind turbine component degradation model has a time resolution of 1 day, the wind model is also only required to have 1 day resolution. Therefore, in the final stage, a wind profile was built using 1 day averaged data, which matches the overall model resolution: the ACF and PACF are plotted in Figure 17 and Figure 18. Clearly Figure 17 suggests that a much lower order AR model will be adequate for a daily resolution wind model than for hourly resolution, because only two ACF coefficients are larger that 1 standard deviation as compared with 40 in Figure 15.

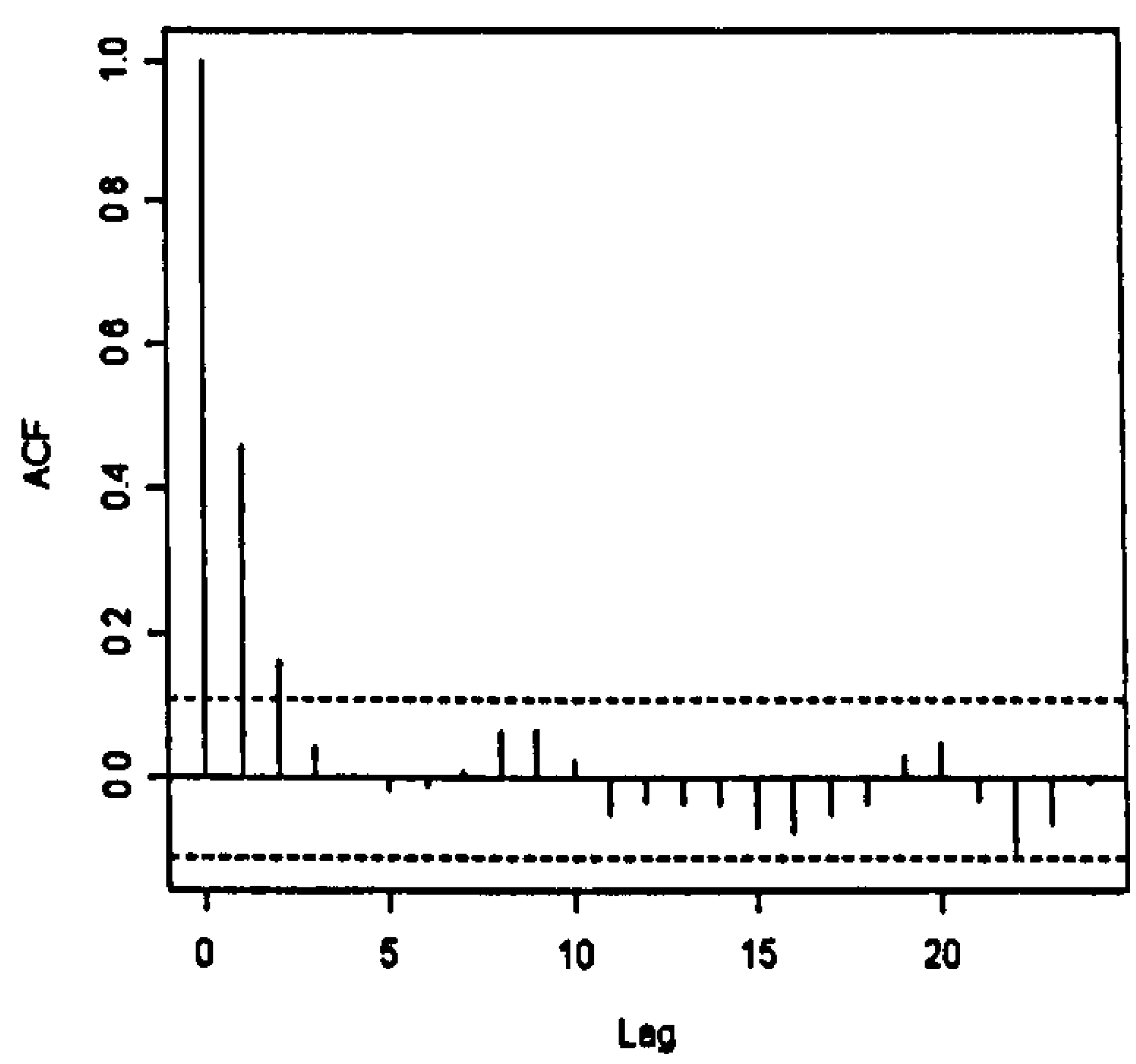

Figure 17: Autocorrelation function at time resolution of 1 day

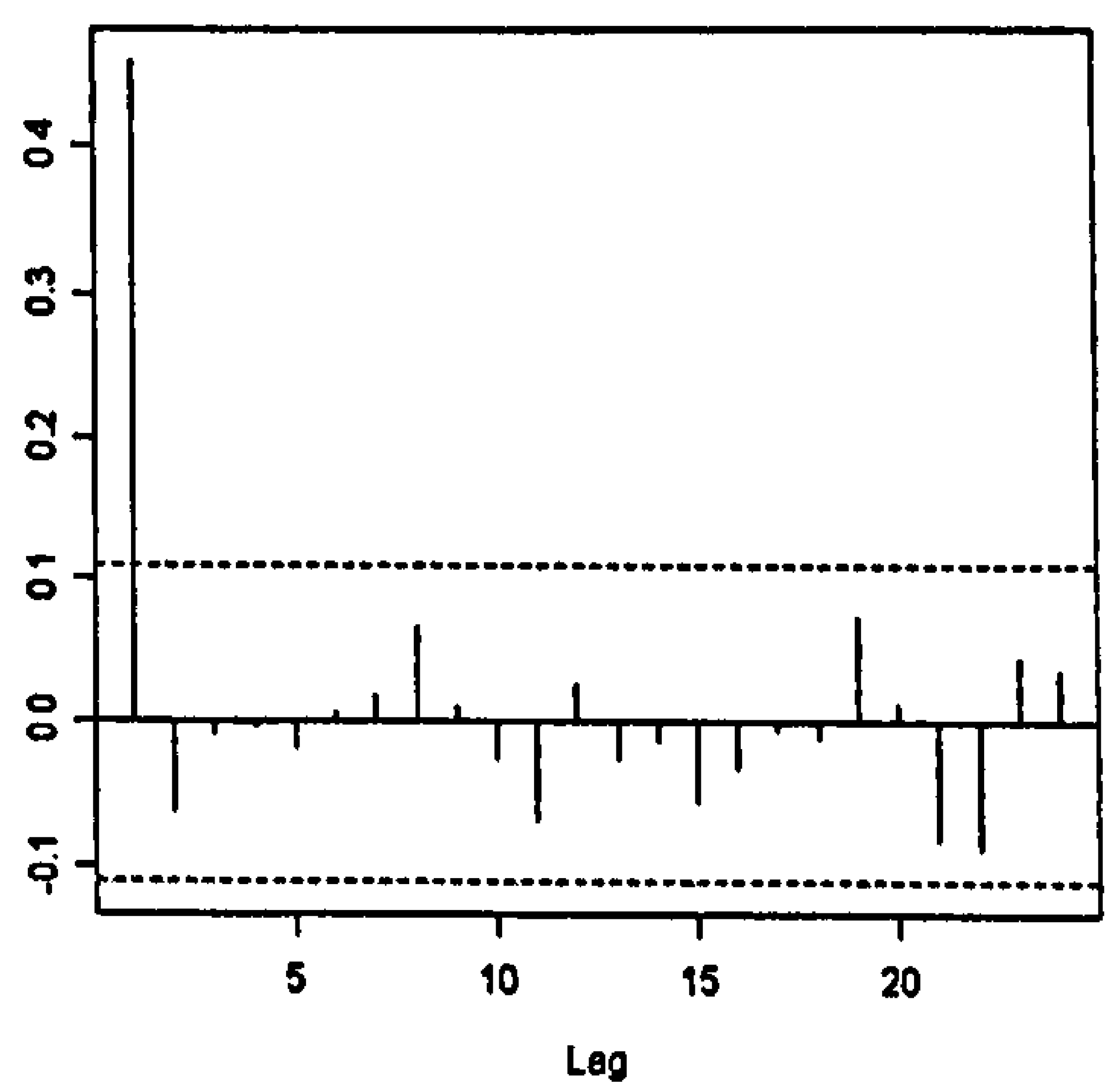

Figure 18: Partial Autocorrelation function at time resolution of 1 day

These two characteristic plots of ACF and PACF in Figure 17 and Figure 18 can be used in conjunction with a set of heuristics to classify the AR model (Wang & McDonald, 1994 p13) – these heuristics are re-created in Table 13.

Model	ACF	PACF
AR(1)	Exponential or oscillatory decay	$\emptyset_{kk} = 0$ for $k > 1$
AR(2)	Exponential or sinusoidal decay	$\emptyset_{kk} = 0$ for $k > 2$
AR(p)	Exponential and/or sinusoidal decay	$\emptyset_{kk} = 0$ for $k > p$

Table 13: Rules for Classification of Auto Regressive Model

Figure 17 (ACF) showed exponential decay behaviour, while the PACF in Figure 18 dropped off to approximately 0 after 1 time lag (i.e. PACF coefficients were less than one standard deviation). Therefore the appropriate model for the wind speed data set examined in this thesis according to Table 13 is an AR(1) model. The fact that only one parameter has to be estimated speeds up the modelling process and limits the complexity of simulating the model when the parameters have been estimated. The quantification of these parameters is discussed and demonstrated in section 4.2.1.

Finally, it is important to contextualise the use of the AR(1) model in terms of data availability. Most time series data are available for many numbers of successive 'periods' – e.g. financial data for many years trading. In the case of wind profile the period is 1 year, which takes into account the seasonality of the data (e.g. in the UK the wind tends to blow harder in winter). Unfortunately if two or more years of data are not available, seasonal trends cannot be distinguished from other effects. Common practice when dealing with seasonal data would involve the removal of the seasonal trend by fitting a time(season)-dependent function to it and then subtracting this function from all time series values – in much the same way as the mean is subtracted from each time series value in equation 25 (z_{t-1}-μ). Then the model is fitted to this modified data set, and afterwards when simulating the model, the trend is added along with the mean value (see equation 25).

Therefore, although the data fit into the AR(1) model, ideally two or more years of data would be analysed so that the seasonal trend could be taken account of. This may have negative implications for the realism of the model, particularly offshore where the seasonality of the wind speed is expected to be a significant factor in maintenance planning.

As a final point, it is noted that a purely autoregressive approach will not reproduce the Weibull-distributed wind speeds that are commonly observed over long-term wind speed measurement. Rather, a Gaussian distribution will be re-produced because the process is essentially being driven by white noise (a_t). This will have the effect of losing some of the extreme high-wind events at the 'tail' of the Weibull distribution. There are two anticipated effects as a result. Firstly, the electricity generation estimates and capacity factor generated by the model may be slightly under-estimated. Secondly the maintenance actions may not be as frequently constrained by wind speed as in a real situation. It is also noted, however, that these effects have a low probability of occurrence and their impact on evaluation of maintenance strategies (TBM, CBM), as examined in this thesis, is thus small.

3.3.2 Wind Turbine Power Characteristic

The amount of theoretical energy in the wind – measured in joules – can be deduced by analysing the classical equation for kinetic energy, E_k, which relates kinetic energy to mass m and velocity v (equation 31). It can be observed that the mass of air moving through a wind turbine rotor (see Figure 19) in one second, m_{air}, is proportional to its swept area, air density ρ and velocity v as expressed in equation 32. Substituting equation 32 into equation 31 gives equation 33, the amount of theoretical energy in the wind.

A wind turbine is essentially a kinetic-mechanical-electrical energy conversion system, and clearly no electro-mechanical system will be 100% efficient in energy conversion due to losses in the system (friction, heat, noise, copper losses etc.). Therefore equation 33 has to be further modified by multiplying by a co-efficient of performance *Cp*. This co-efficient takes account of the losses in the conversion process, and is not constant: it varies over the wind speed range and depends on the wind turbine in question.

$$E_k = \frac{1}{2} m v^2 \tag{31}$$

$$m_{air} = \rho \pi r^2 v \tag{32}$$

$$E_k = \frac{1}{2} \rho \pi r^2 v^3 (\times C_p) \tag{33}$$

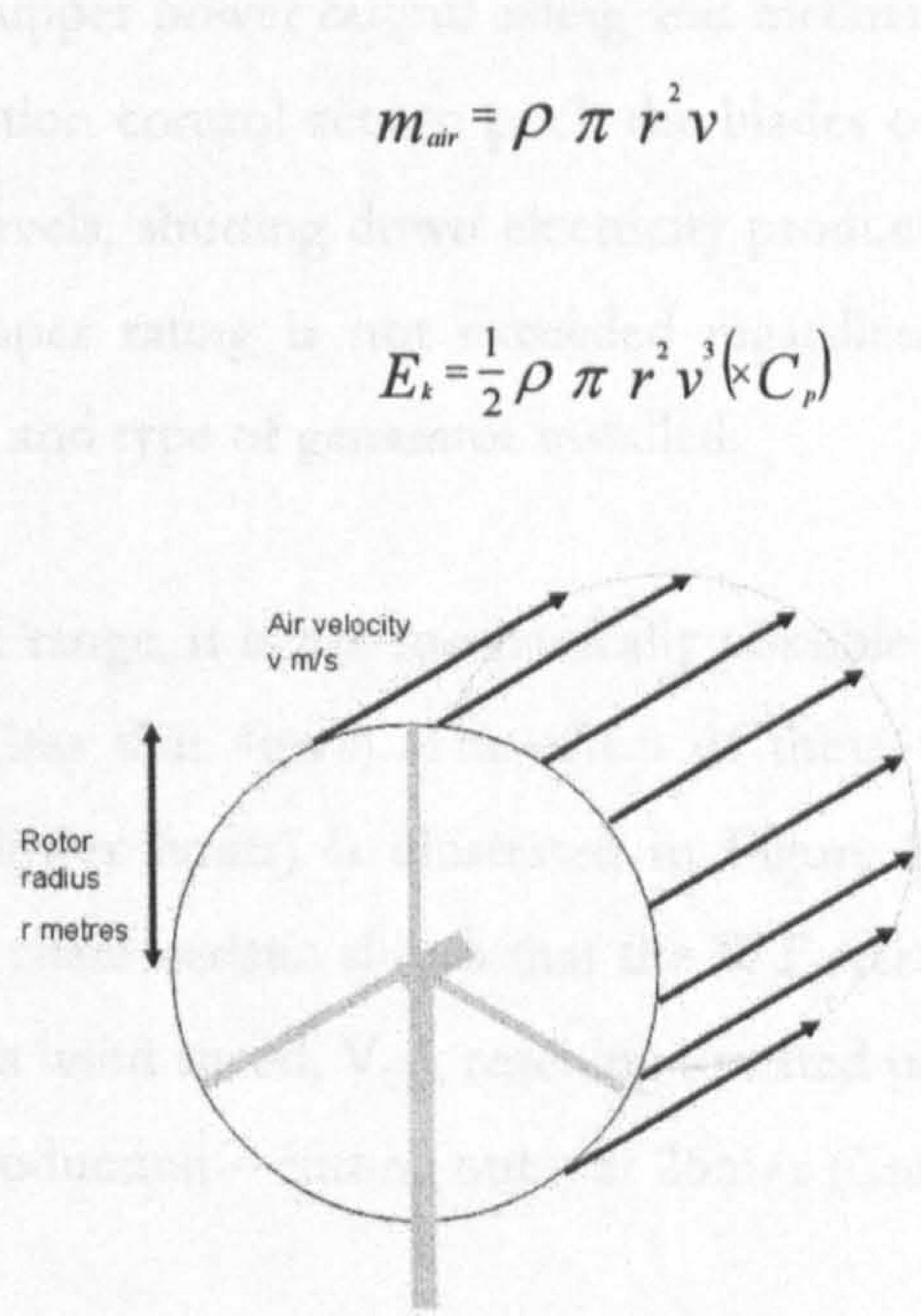

Figure 19: Schematic of Air Flow Through a Wind Turbine Rotor

Thus, the wind turbine rotor can only physically convert a proportion of the available theoretical energy into torque. This was first observed by Betz who predicted the maximum efficiency of the conversion process to be roughly 59% (Boyle 2004, p262) – this upper limit is know as the Betz limit. Taking the Betz limit into account, Figure 20 plots the maximum recoverable energy in the wind for various typical wind turbine rotor diameters, ø.

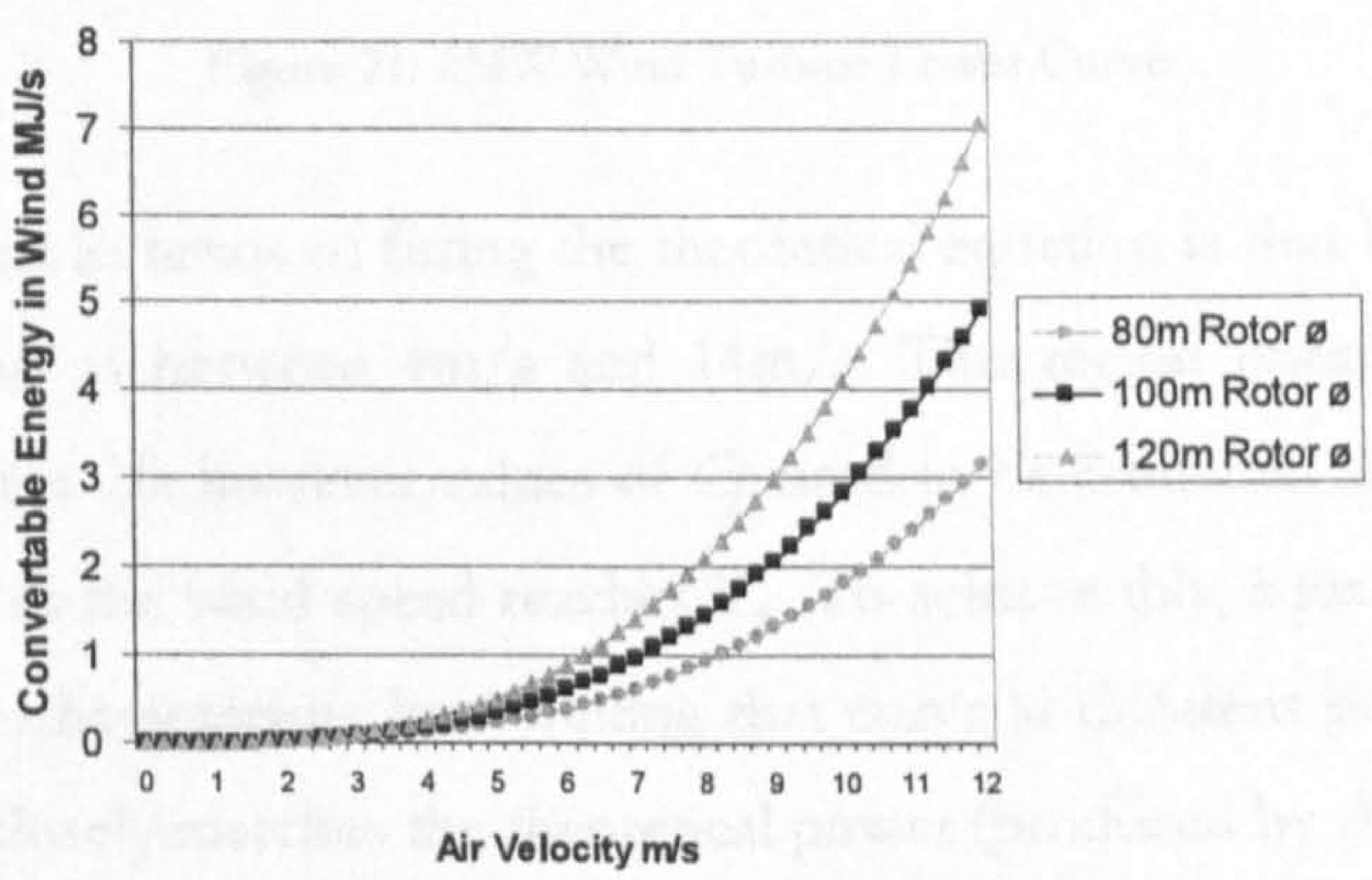

Figure 20: Maximum Recoverable Energy in the Wind According to Betzs' Limit

Wind turbines are designed to extract as much of the available energy as possible, however it is simply not practical to build an electro-mechanical system to withstand the entire wind speed range. Therefore an upper power output rating and mechanical protection control are built in. Mechanical protection control acts to pitch the blades out of the wind if the wind speed reaches dangerous levels, shutting down electricity production until the wind returns to nominal levels. The upper rating is not exceeded regardless of the wind speed, and depends on the WT design and type of generator installed.

Similarly for the low speed range, it is not mechanically possible to extract energy from the wind at very low speeds (less that 4m/s). The effect of these various factors (theoretical characteristic, upper and lower limits) is illustrated in Figure 21, which is a 2MW wind turbine power curve. This characteristic shows that the WT starts generating electricity at a wind speed of 4m/s (Cut in wind speed, V_{CI}), reaching its rated power at 14m/s (Rated wind speed, V_R) and stopping production – cutting out – at 25m/s (Cut out wind speed, V_{CO}).

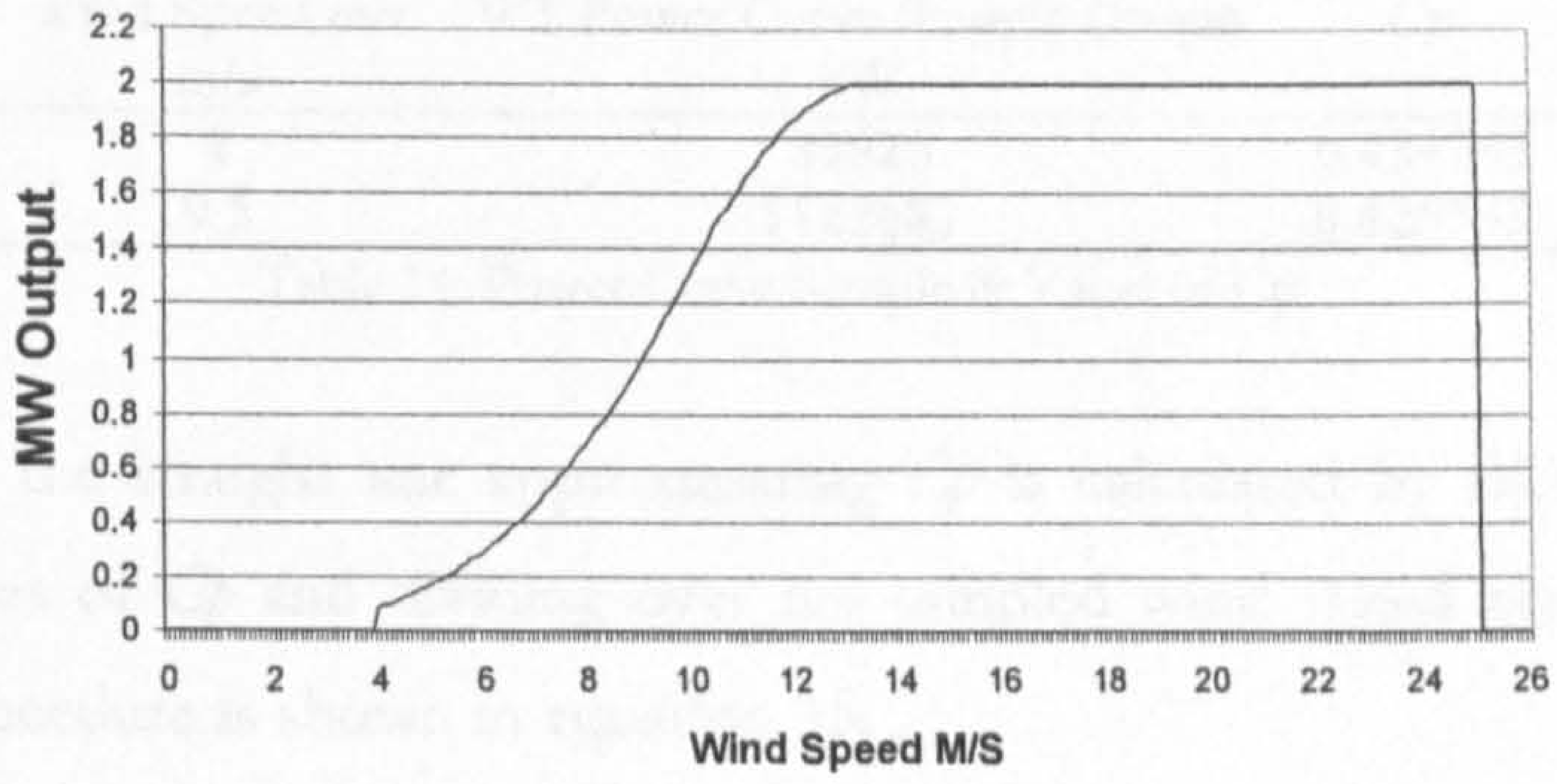

Figure 21: 2MW Wind Turbine Power Curve

The region of interest in terms of fitting the theoretical equation is that between V_{CI} and V_R, for this example that is between 4m/s and 14m/s. This region resembles the theoretical characteristic in Figure 20: however values of *Cp* need to be estimated as they are clearly not constant, especially as the wind speed reaches V_R. To achieve this, equation 33 can be fitted to any power curve characteristic by sampling that curve at different points and choosing a value of *Cp* which closely matches the theoretical power (produced by the equation) with the sampled power curve.

For any points in-between the sampled power curve values, *Cp* can be approximated as a linear function of the distance between the two samples – following the well known linear equation 34. For this case, *x* is equivalent to wind speed and *y* is the value of *Cp*. The gradient of the assumed linear function of *Cp* is *m*, and c is the value of *Cp* at 4m/s.

$$y = m\,x + c \tag{34}$$

Application of this concept to an actual power curve is best illustrated by a simple example. The 2MW power curve previously described can be sampled at any two points on the wind speed range – for this example, points at 4m/s and 9.5m/s are chosen. These points are used to characterise the power curve between 4m/s and 9.5m/s. The power output and resultant value of *Cp* needed to match the equation with the power curve are displayed in Table 14.

Wind Speed m/s m/s	WT Power Curve Sample Output kW	*Cp*
4	85626	0.434783
9.5	1122687	0.425532

Table 14: Power Curve Sample & Value of Cp

The 'gradient' of the straight line approximating *Cp* is calculated by taking the difference between the values of *Cp* and dividing over the sampled wind speed range. The equation governing this procedure is shown in equation 35.

$$m_{C_p} = \frac{Cp_{4m/s} - Cp_{9.5m/s}}{WS_{4m/s} - WS_{9.5m/s}} \tag{35}$$

An application of equation 35 using the Table 14 values is shown below. The gradient in this case is calculated as -0.001682. Using this calculated gradient, *Cp* at any wind speed point in-between 4 to 9.5m/s can be estimated by applying the formula for a straight line (see equation 34).

$$m_{C_p} = \frac{Cp_{4m/s} - Cp_{9.5m/s}}{WS_{4m/s} - WS_{9.5m/s}} = \frac{0.434783 - 0.425532}{4 - 9.5} = \frac{0.009251}{-5.5} = -0.001682$$

In this way, values of *Cp* for other samples in-between 4 and 9.5 m/s can be accurately calculated. The illustrative examples below show the calculations for *Cp* at 6m/s and 8m/s. Utilising these values for *Cp* and applying equation 33, the power curve for intermediate samples can be plotted.

$$C_p@6m/s = m_{C_p}\Delta x + C_p@4m/s = -0.001682 \times (6-4) + 0.434783 = 0.431419$$

$$C_p@8m/s = m_{C_p}\Delta x + C_p@4m/s = -0.001682 \times (8-4) + 0.434783 = 0.428055$$

Figure 22 illustrates both the modelled linear reduction of *Cp* over the wind speed range4m/s – 9.5m/s and the power curve which results from application of equation 33. Modelling of *Cp* as a linear function results in an adequate representation of the non-linear region of the power curve. This can be achieved without having to carry out a very large number of power curve samples.

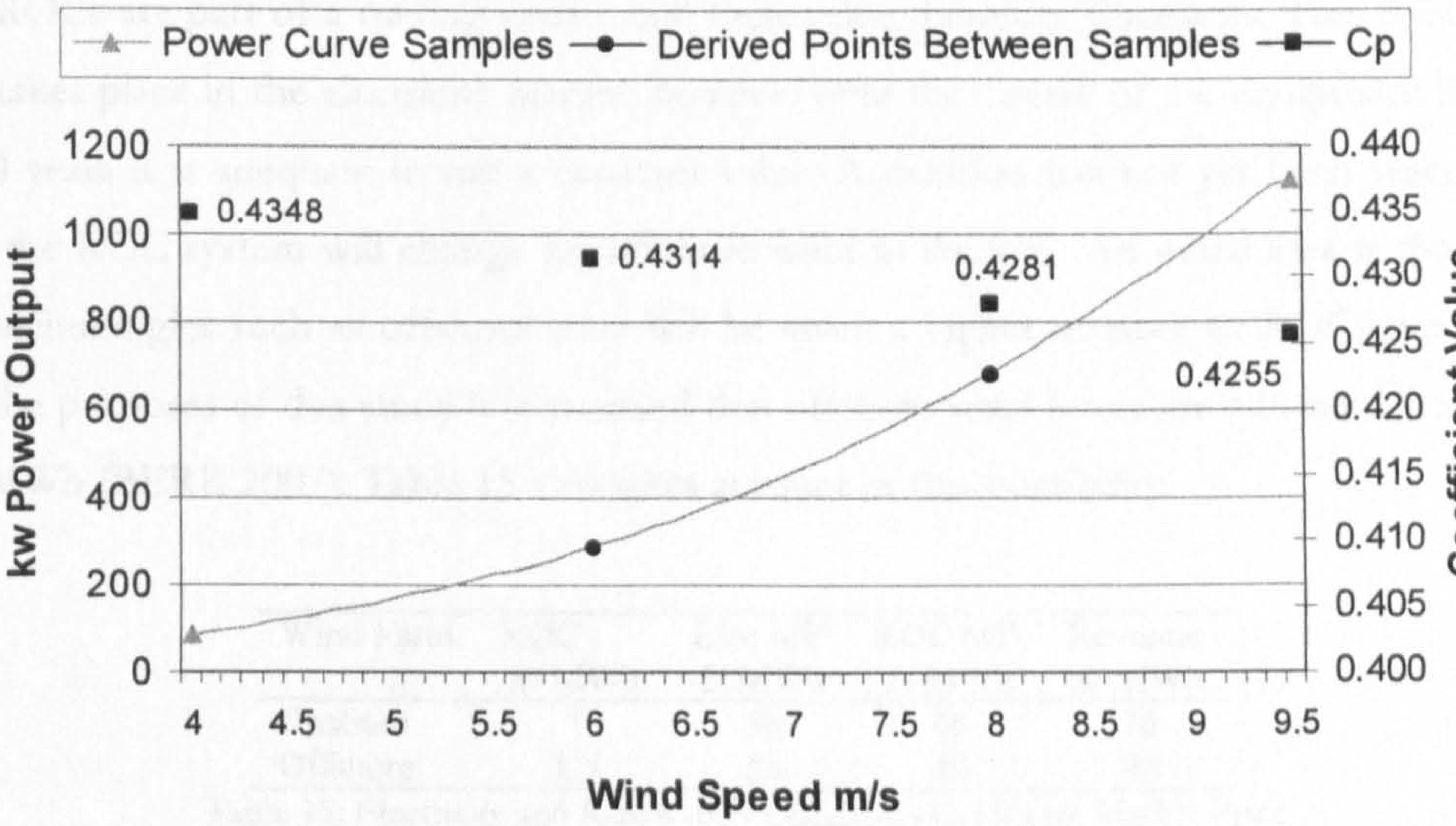

Figure 22: Fitting Energy Yield Equation to Wind Turbine Power Curve

Using this method, the power curve can be generated over the entire wind speed range from a relatively small number of samples. This is advantageous since manufacturers' power curves are often plotted in data sheets, but the actual data tables are not included. Therefore, using this method it is relatively easy to re-create power curves from a manufacturers' data sheet and include it in the analysis of various wind profiles.

3.3.3 Electricity and Renewable Obligation Certificates Market Price

The economic yield of a wind farm depends on the mechanisms in place to incentivise renewable-generated electricity, which varies depending on the energy policy of the individual country. For the purposes of this thesis, the UK renewables obligation system is used as the policy instrument: however modelling of a feed in tariff (typically used in Europe and U.S.A.) is equally straightforward. This means that as well as generating income per Mega-Watt hour (MWh) of electricity produced (MP_{elec}), the wind turbine will accumulate renewable obligation certificates (ROCs) and is also able to get market price for these (MP_{roc}).

Typical values for the market prices are illustrated in Table 15, although it should be noted that ROCs are part of a trading system and their value therefore fluctuates. This fluctuation also takes place in the electricity market: however over the course of the equipment lifetime of 20 years it is adequate to use a constant value. A decision has not yet been reached on how the ROC system will change for offshore wind in the UK. An initial idea is that high-risk technologies such as offshore wind will be given a higher number of ROCs per MWh. For the purposes of this study it is assumed that offshore wind farms are allocated 1.5 ROCs per MWh (BERR 2007): Table 15 also takes account of this possibility.

Wind Farm	ROC #/MWh	Elec MP £/MWh	ROC MP £/MWh	Revenue £/MWh
Onshore	1	36	40	76
Offshore	1.5	36	40	96

Table 15: Electricity and Renewables Obligation Certificate Market Price

The theoretical annual energy yield (Y_{ann}, MWh) produced by a wind turbine is a function of annual capacity factor (CF_{ann}, %), WT generator rating (G, MW) and annual availability (A_{ann}, %). Noting that 8760 is the number of hours in one year, equation 36 characterises the annual energy yield utilising the variables mentioned.

$$Y_{ann} = CF_{ann} \times G \times A_{ann} \times 8760 \tag{36}$$

Based on this, the amount of theoretical revenue generated per annum (R_{ann} £) by a wind turbine is calculated on the basis of energy yield and the market prices of electricity and ROCs (MP_{elec}, MP_{roc}). Equation 37 shows the simple nature of the relationship used to obtain economic WT yield.

$$R_{ann} = Y_{ann} \times (MP_{elec} + MP_{ROC}) \tag{37}$$

Clearly the time period can be altered to calculate the yield and revenue for any time step of interest – not just annual values. The advantage of these simple calculations is that they provide a useful method to validate the models proposed in this thesis, since the outputs generated via MCS can be compared directly with ball-park figures derived from equations 36 and 37.

3.4 Maintenance Modelling

The final level of the modelling process as outlined in Figure 6 is the asset management policy of the wind farm operator, the techno-economic impact of which forms the basis of the analysis in this thesis. Since the Markov model has been chosen as the most suitable representation of the WT components, maintenance effects in particular must be quantified with respect to the Markov model. This is another area where Anders, Endrenyi and associates have published prolifically.

Most significantly, Endrenyi et al. (2001) presented a review of the most frequently used maintenance strategies and showed that the most widespread strategy is fixed interval maintenance with breakdown corrections as required (TBM). The authors performed a survey of electrical utilities and deduced that methods based on mathematical modelling are hardly ever used, and generally utilities do not perform predictive maintenance exclusively. They identify the most effective diagnostic tools as gas and oil analysis, surge measurement and vibration analysis for rotating machines. In order to model deterioration processes two methods are identified: duration-based and physical-based. The main advantages of a predictive maintenance regime as identified by the authors are better outage scheduling, increased operational flexibility, and more efficient use of fuel and spare parts. A Markov process was adopted by the authors and maintenance modelled in various ways within this framework.

There are several possible methods for modelling maintenance in the Markov model. This is one area of modelling where a high number of assumptions are usually made because it is very difficult to physically quantify the effects of maintenance actions. Some key distinctions of maintenance models are explored below: these are expanded on in the next section.

- Perfect or imperfect maintenance i.e. technical consequences of maintenance
- Mechanism for capturing downtime after failure or repair
- Modelling economic consequences of maintenance, failure & repair
- Modelling TBM and CBM

3.4.1 Technical Impact of Maintenance

The effectiveness of maintenance actions and resultant impact on performance of assets is a subject of debate in industrial circles - as outlined in the keynote paper by Endrenyi et al. (2001). It is therefore no surprise that mathematical modelling of such processes is also a contentious issue. The simplest method of modelling maintenance actions is that the equipment is restored to 'as good as new' condition – also known as perfect maintenance. Imperfect maintenance models characterise actions which restore the asset to an operational but imperfect condition state.

Consider again the ergodic, generic system in Figure 8 (reproduced below) and define s_1, s_2 and s_n as fully up, deteriorated and failed states respectively. In this case if the system were to transit to failure – s_n – then perfect (reactive) maintenance actions would restore the system to s_1 (fully up) whereas imperfect maintenance would restore the system to s_2 (deteriorated).

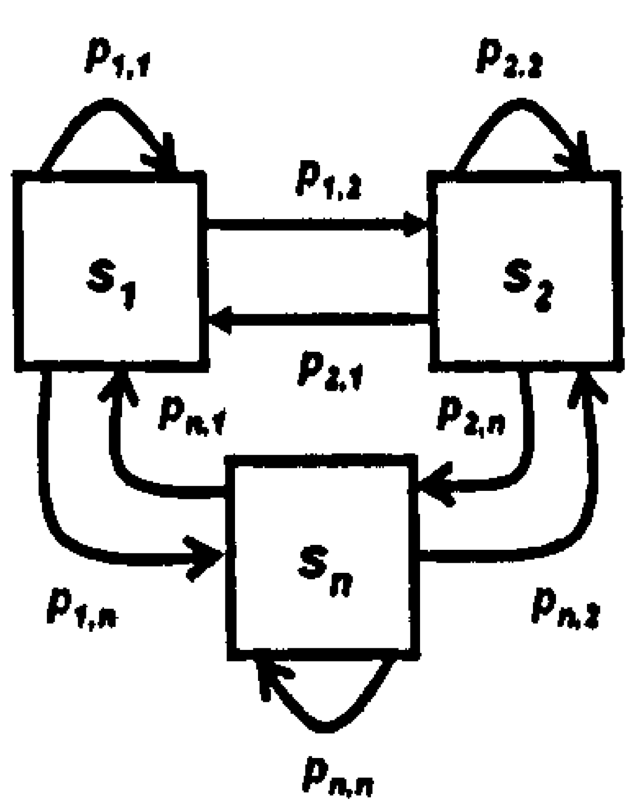

Figure 8: Generic Markov Chain (Reproduced from page 65)

Using MCS to model the planned maintenance policies makes the representation straightforward. In the case of TBM, a counter is simply set up and the system runs through its non-ergodic Markov-based condition trajectory until the maintenance interval is reached. At this point maintenance is applied, the deteriorated system being restored to the fully up state, incurring the relevant costs and downtime. CBM is more complex, but the idea of counting until a maintenance interval has expired and then applying maintenance is the cornerstone of modelling both TBM and CBM. The key difference with CBM is that the maintenance interval is coupled with the system condition.

3.4.2 Mechanisms for Modelling Downtime after Failure and Repair

There are two main methods of modelling the physical possibility of maintenance in a Markov model. The method most used in analytically-solved models is maintenance as a repair rate or repair probability (the continuous and discrete-time cases). The alternative is to model failure states as absorbing states which last for a modelled amount of time (deterministic or probabilistic) and then re-start the Markov model either in fully up (perfect maintenance) or deteriorated state (imperfect maintenance).

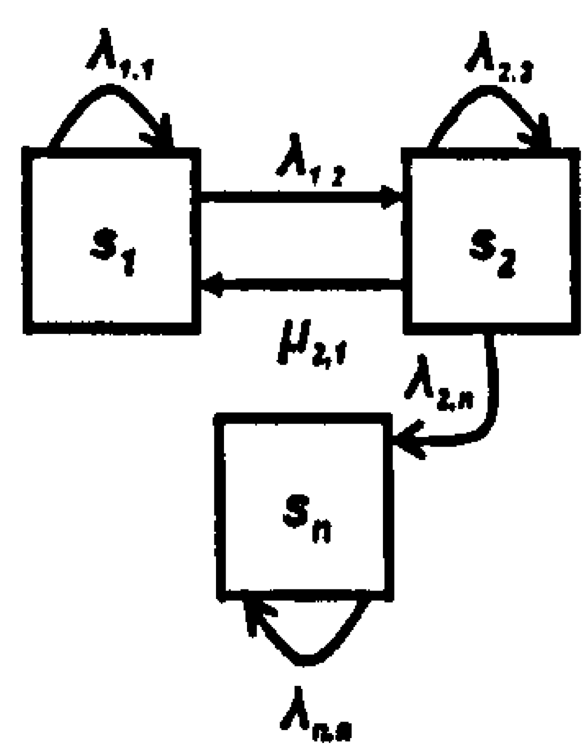

Figure 11: Markov Process (Reproduced from page 75)

The Markov process reproduced in Figure 11 shows how the repair rate μ_{21} is used to model repair between s_2 and s_1. This could also apply to s_n if it were modelled as a failed equipment state, in which case the repair rate would be μ_{n1}. The advantage of this type of maintenance model is that it fits nicely into the Markov model framework and can thus form part of an elegant analytical solution. For this reason, repair rates are popular in the literature: however it is interesting to note that many papers which employ this method often have a mathematical rather than engineering focus. Since the focus of this thesis is very much engineering analysis, other methods for downtime modelling are considered.

The main alternative to repair rate/probability for repair modelling is to model a downtime when the equipment reaches failed system states defined as absorbing states. This downtime can be deterministic or probabilistic in nature: in practice this is dependent on the available data. In the case of deterministic downtime, a counter is devised which counts up to a maximum value e.g. 7 days – throughout this time (t_{sfail}=1…7) the equipment remains in the down state, s_{fail}.

Figure 23 illustrates the comparison between failure rate repair modelling and absorbing state/deterministic downtime modelling for 7 days of downtime at a time resolution of 1 day. In the probabilistic case, the maximum downtime duration is defined by a suitable probability distribution rather than a constant (e.g. 7 days). After the downtime has elapsed, the equipment is restored to the relevant functional state.

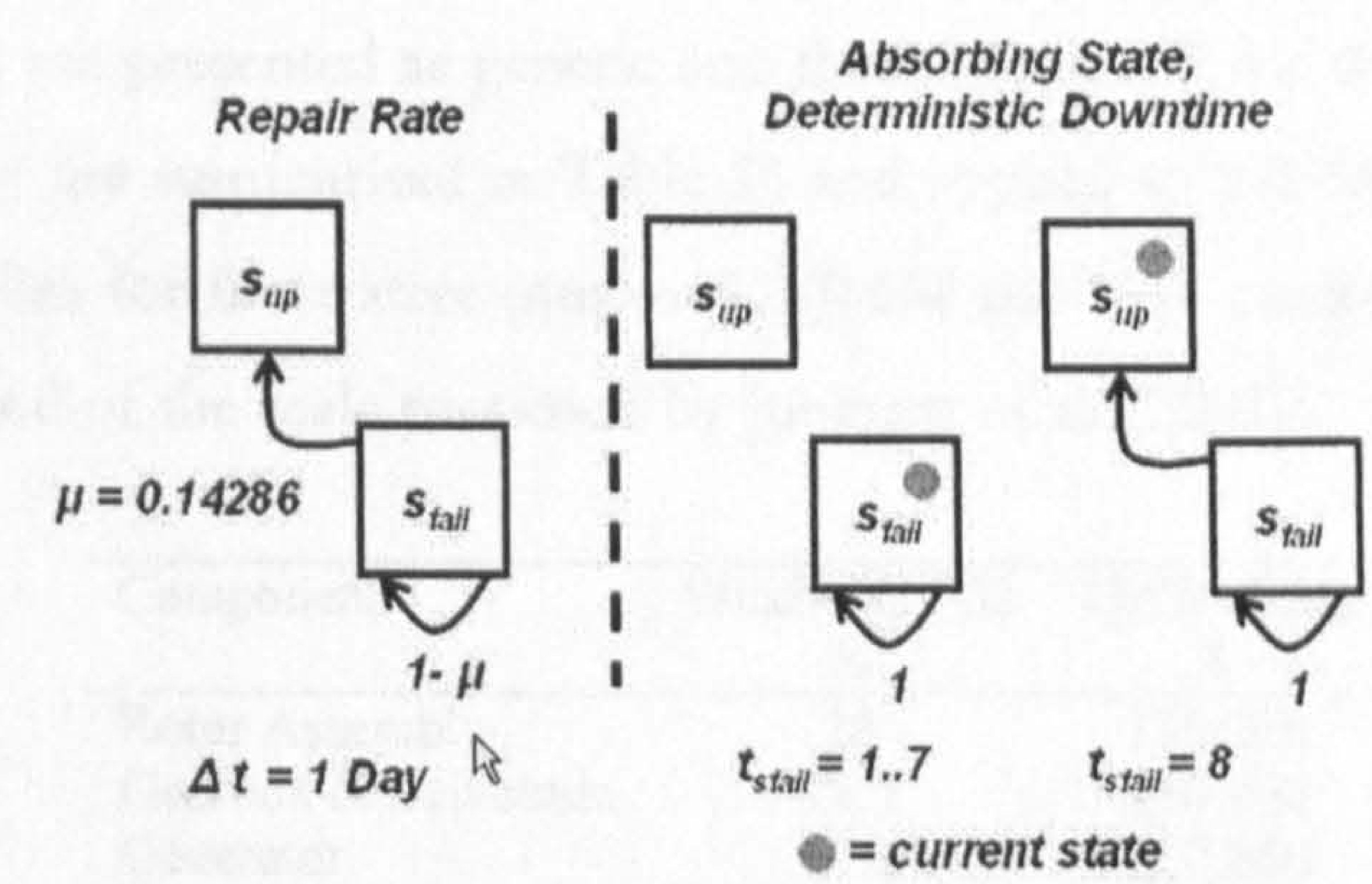

Figure 23: Modelling Repair as a Transition Probability/Rate and an Absorbing State with Deterministic Downtime

The advantage of the absorbing state/deterministic downtime modelling approach is that it gives the modeller more control over how different repairs and replacements are modelled. For example, a severe failure requiring a replacement part can be modelled with a long downtime, whereas a trivial repair might have much shorter duration. When combined with MCS this becomes an extremely powerful tool, the key characteristic being the adaptability of the combined approach, which is very suitable for capturing operational constraints such as maintenance duration. Therefore the method of modelling repair and downtime adopted in this thesis is use of absorbing states and deterministic downtime.

3.4.3 Economic Impact of Maintenance, Failure & Repair

The economic impact of maintenance actions comprise the capital cost or repair cost of the failed component, the cost of maintenance personnel and cost of specialised equipment such as heavy cranes, which are often hired as needed by the wind farm operator rather than owned. Additionally, the lost revenue (see equation 36 & equation 37) while in the non-functional state contributes to the economic implications of maintenance or failure.

The largest of these individual costs are the capital costs (C_{CAP}) of wind turbine components. These have been quantified in various publications. In particular, the WindPACT study recently conducted by NREL (Poore & Lettenmaier, 2003 p82) compiled costs of WT components is some detail. Simple rules to derive component costs as a percentage of overall WT capital cost derived from this study are summarised by Sterzinger & Svrcek (2004 p53) – these are presented as generic and therefore useful for this study. The findings of the NREL study are summarised in Table 16 and applied to a 2MW wind turbine with a capital cost of £1.2m for illustrative purposes (£0.6M per MW capital cost was assumed – towards the high end of the scale proposed by Juninger et al. (2004)).

Component	WindPACT 03 %	2MW Costs £
Rotor Assembly	28	336,000
Gearbox & Drivetrain	21.7	260,400
Generator	17.3	207,600
Tower & Foundation	7	84,000
Other Nacelle	26	312,000
Total	100	1,200,00

Table 16: Capital Costs of Major Wind Turbine Components

For major repairs or outright component replacements, lifting devices are needed for hoisting components up to the height of the nacelle. These devices are highly specialised, and their use incurs significant cost. A number of sources were used for estimates of crane hire costs (see Table 17) including industry articles (*Anon, 2006 pp24) expert estimates (**Concerted Action on Offshore Wind Energy in Europe, 2001) and UK government reports (***Way & Bowerman, 2003 pp34). The large disparity for the offshore cases represents the sparsity of data, probably due to the sensitivity of operators to this issue.

Location	Mobilisation £	Crane Type	Hire Rate £ per week	Total cost per 1 week action C_{E_f} £
Onshore*	Unknown	Telescopic Crawler – Hire	1,500	1,500
Offshore**	Unknown	Jack-Up Vessel – Hire	15,000	15,000
Offshore***	50,000	Telescopic Crawler – Installation hire	11,000	61,000

Table 17: Equipment Costs

The costs of maintenance staff have been quantified by *Nilsson & Bertling (2007) and **Andrawus et al. (2006). Their figures are re-stated in Table 18 as the total labour cost (C_{LAB}) per maintenance action, for use in the studies proposed in this thesis. Clearly these values are very small compared with component replacement costs: however labour costs will be incurred for any fault, no matter how trivial, and therefore are incurred more frequently.

Company – Maintenance Type	Labour Time Hours	Labour Cost £ per hour	Total Labour cost per action C_{LAB} £
Vattenfall – All*	24	32.4	777
Elsam – Planned*	24	18.75	450
Elsam – Unplanned*	24	21.25	510
SSE**	24	50	1,200

Table 18: Labour Costs

The costs summarised in this section are fairly generic, however some of them may be modified depending on the type of maintenance conducted. The simplest case is reactive maintenance, when a component is returned to service after an outright failure. In this case, the outage is not planned and therefore the duration of the outage duration will be longer than a planned outage, resulting in higher lost revenue. Additionally, outright failures tend to be severe: therefore the cost of the repair is likely to be high.

The cost of individual repairs is very difficult to quantify, however some simple rules can be adopted to estimate repair and replacement costs. In the most simplistic case, all failures result in a component replacement. In this case the economic impact $C_{O\&M}$ is simply the component replacement cost C_{CAP} plus labour C_{LAB}, equipment hire C_{E_q} and lost revenue R_{LOST} all multiplied by the frequency of failure λ of that component. If a spare is not held the downtime may be very large, especially for more specialised components with long lead-times, meaning R_{LOST} will be large. The generic case is shown in equation 38, with a proportion of failures, β, resulting in a replacement and a proportion are repairable (β – 1). Repairable failures only incur a fraction (a) of the replacement cost (C_{CAP}).

$$C_{O\&M} = \beta \cdot \lambda \times \left(C_{CAP} + C_{LAB} + C_{E_q} + R_{LOST}\right) + \left(1-\beta\right) \cdot \lambda \times \left(\alpha \cdot C_{CAP} + C_{LAB} + C_{E_q} + R_{LOST}\right) \quad (38)$$

In the simplistic case of all failures resulting in a replacement, $\beta = 1$ and equation 38 simplifies to $C_{O\&M} = \lambda\ (C_{CAP} + C_{LAB} + C_{E_q} + R_{LOST})$. An estimate of $C_{O\&M}$ can be made by plugging in values to this equation. For example: a 2MW WT gearbox failure might occur with annual probability $\lambda = 0.1$, and $C_{CAP} =$ £100,000 $C_{LAB} =$ £510 $C_{E_q} =$ £1,500. On the basis of a 30 day outage and 30% capacity factor, $R_{LOST} =$ £32,832, and:

$$C_{O\&M} = 0.1 \times (100{,}000 + 510 + 1{,}500 + 32{,}832) = £13{,}484$$

On the other hand, a repair may be adequate in some cases of outright failure. Failure data can be analysed to identify which proportion of outright failures result in replacement of the component, for example Ribrant & Bertling (2007) showed that 59% of gearbox failures resulted in a replacement: this means that β in equation 38 is equal to 0.59. Alternatively, these figures could be estimated from expert opinion. In this case the downtime will be the time taken to schedule and complete the maintenance action, and so R_{LOST} is potentially much smaller.

It is very unlikely that a repair will cost as much as a component replacement, and in the absence of repair costs which are very elusive, a proportion, α, of the component replacement capital cost C_{CAP} can be used. Taking $\alpha = 0.1$, assuming repair downtime is 7 days and applying equation 38:

$$C_{O\&M} = 0.59 \times 0.1 \times (100{,}000 + 510 + 1{,}500 + 32{,}832) + 0.41 \cdot 0.1 \times (0.1 \cdot 100{,}000 + 510 + 1{,}500 + 7660)$$

$$\therefore C_{O\&M} = 7{,}955 + 806 = £8{,}762$$

Including more detail in the technical and economic modelling of failures clearly impacts on the result of the calculation. Therefore the latter, more detailed approach to modelling failure and repair is adopted in this thesis.

Any maintenance policy will contain an element of reactive maintenance, so the modelling explained so far will certainly form part of the overall maintenance effort. However an operator is unlikely to adopt a solely reactive maintenance policy, as discussed previously. Therefore the next step is to model TBM and CBM.

3.4.4 Modelling Time Based Maintenance and Condition Based Maintenance

The effects of maintenance actions have already been discussed, however implementation of different maintenance policies have yet to be specified. Since most wind farms are maintained according to a TBM policy, this represents the baseline case. Anecdotal evidence from wind farm operators, acquired during this research, indicates that TBM intervals are dependent on physical location and access to the wind farm. In the case of onshore wind farms, the maintenance interval is typically 6 months, corresponding to a maintenance frequency of 2 actions per annum. Offshore access constraints inhibit such frequent maintenance actions and these are therefore restricted to one action per year (every 12 months). It is very straightforward to visualise how such a TBM policy is applied within the MCS framework. Taking the example of a 6 month maintenance interval, – illustrated in Figure 24 – if the model time resolution is 1 day, the Markov chain will be simulated until 182 days have elapsed.

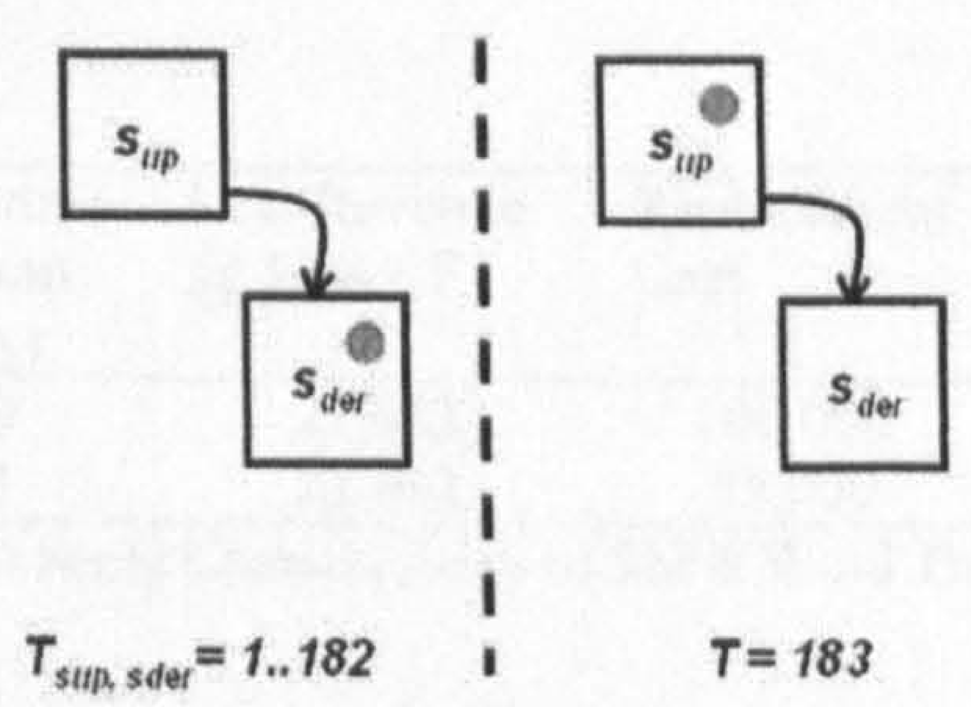

Figure 24: Example of Time-Based Maintenance Applied via MCS

During this time the system may transit to a derated state s_{der}. Then the system is restored to s_{up} and the relevant costs (see previous section on maintenance costs) are deducted. The case of TBM on a gearbox lasting 1 day is illustrated below using equation 38 where $\beta = 0$.

$$C_{O\&M} = (0.1 \cdot 100{,}000 + 510 + 1{,}500 + 1094)$$

$$\therefore C_{O\&M} = £13{,}104$$

Modelling of CBM is more complex than TBM, but is aided by the state-based nature of the Markov model. The key is to couple the Markov condition state with maintenance actions, as CBM is applied in practice, but in a way which realistically balances technical and economic aspects. For example, scheduling a maintenance action the same day as a problem is detected is probably unrealistic and may result in an unrealistically high number of maintenance actions. On the other hand, if the potential failure is identified as being particularly severe, the operator may wish to intervene more urgently than if the potential failure had a low impact.

In the case of a wind turbine this can be appreciated by comparing two sub-components with different failure severity. A 2MW wind turbine contains a generator and gearbox among its sub-components. The characteristics of these two components for this rating of turbine are derived from (McMillan & Ault, 2007) and are summarised in Table 19. Assume that the probability of failure Pr_{fail} (over a 1 year time step) having detected an incipient fault is 0.1 for both components. This is roughly equivalent to the case in equation 38 where $\beta = 1$ (for the moment C_{LAB} & C_{E_q} are neglected).

Component	Pr_{fail} Probability	Downtime Duration Days	Lost Revenue @ 30% CF £	Replacement Cost £	Total Outage Cost (TOC) £	Risk Pr_{fail} X TOC £
Gearbox	0.1	30	32,832	100,000	132,832	13,283
Generator	0.1	21	22,982	55,000	77,982	7,798

Table 19: Outage Severity Characteristics of 2MW Wind Turbine Components

It can be seen that the total cost of each outage (TOC) differs considerably. The product of TOC and the probability of the event is defined as the risk, which is the final column of Table 19. For this work, the risk is used to set the maintenance 'urgency': that is the time between detection of a fault and the scheduling of a preventive maintenance action (i.e. CBM). This is analogous to the fixed time in the TBM model except, of course, that the time is coupled with condition. Clearly in the case of the data in Table 19 the gearbox maintenance would be of more immediate concern than the generator because the (economic) risk associated with a gearbox failure is almost double the magnitude of the generator risk. How the maintenance interval is set in light of this risk metric will be defined late in the thesis in chapter 4.

3.5 Chapter 3 Summary: Selection of Models for Wind Turbine Processes

The information presented in this chapter has illustrated the myriad of modelling options available to represent the three key aspects of wind farm operation as shown in Figure 6 (WT component deterioration and failure, wind speed and energy yield, and asset management policies). The methodology proposed in this thesis extracts the most useful combination of these individual models and combines them, resulting in a framework capable of answering the research questions posed in the introduction. Table 20 outlines the selection of models adopted for the rest of the thesis.

Model Aspect	Type of Model Selected
Component Deterioration	Markov Chain solved via MCS
Failure Modelling	Absorbing states, Markov chain renewed after downtime.
Downtime Model	Deterministic time constant
Wind Speed	Autoregressive Time Series, simulated via MCS
Power Curve	Energy yield equation fitted to sampled power curve, linear interpolation
Reactive Maintenance	Restore Markov Chain to up state after downtime count – dependent on failure severity (repair or replacement).
Time-Based Maintenance	Restore Markov Chain to fully up state after deterministic wait time.
Condition-Based Maintenance	Restore Markov Chain to fully up state with repair urgency dependent on system condition status

Table 20: Selection of Models for Application to Techno-Economic Benefit Evaluation of Wind Farm Condition Monitoring

The models used to characterise the processes of interest have been selected, based on various aspects of their suitability which have been explained in this chapter. With a well-defined modelling framework in place, the next chapter explains how the methodology is applied in practice, including issues such as data sourcing, parameter estimation and interaction between the models.

3.6 Chapter 3 References

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4 Methodology and Application

The previous chapters have explained the rationale behind the choice and particular combination of models adopted in this thesis. Using Markov chains for component deterioration, time series models for wind speed, and Monte Carlo methods for simulation of the asset condition trajectory, constraints and maintenance actions provides a flexible and practical framework to capture the wind farm processes of interest. However, the models require to be defined in terms of which components are represented, how parameters are estimated and which constraints are applied. This chapter provides detail and examples of how these key modelling decisions are taken, and clearly sets out the model development process. Finally, the fully developed models for WT component deterioration, wind profile and maintenance are presented.

4.1 Defining a Markov Chain for Wind Turbine Components

The first questions to be answered when modelling the WT as a Markov chain are which of the WT sub-components should be modelled, and how many states are necessary to represent each component. This defines the number of states in the overall model and enables the modeller to establish which state transitions are possible. The full set of sub-components have been listed earlier in the thesis (see Table 5 and Figure 5), and will be discussed in more detail in the following sections. Clearly the selected components should be those which have a significant impact on the operation of the WT from a techno-economic viewpoint. The decision of which components to include in the Markov chain condition model was based on four factors: these are listed below.

- Expert opinion of wind farm operator
- Failure rate of components
- Impact of component failure – Downtime and component cost
- Applicability of condition monitoring techniques

4.1.1 Expert Opinion of Wind Farm Operator

The operators' interest was in those components whose characteristics made them problematic from a repair/ replacement viewpoint, and also those components with a high technical and economic impact of outage (equivalent to total outage cost in Table 19). Three components in particular were recommended for inclusion in the modelling. These were the generator, gearbox and rotor blades.

The reason for the high significance attributed to these components was expressed qualitatively by the wind farm operator in the points listed below. The fact that the three identified components (generator, gearbox and rotor blades) are complex electrical or mechanical systems in their own right means that they have a high associated cost. Furthermore, at the time of writing there was a significant worldwide supply bottleneck, in particular for gearboxes, due to inadequate global WT manufacturing capability. This has resulted in lengthy lead times, for these three components in particular. Since all three identified component parts are an integral part of the WT drive train, they are all inconveniently located at the top of the WT tower (usually between 60-80m above the base). This makes in-situ repair difficult because of the physical problems of getting heavy repair equipment to the top of the tower as well as wind-induced nacelle oscillations which make the act of carrying out the repairs more difficult and dangerous in high winds. If a replacement of any of the three components (generator, gearbox and rotor blades) is required, the large weight and size of the components means that specialised cranes are needed which in turn need low wind conditions to operate. This need for suitable weather conditions can complicate component replacement actions, further extending the WT downtime.

1. High capital cost and long lead-time for replacement
2. Difficulty in repairing in-situ
3. Large physical size and weight
4. Position at top of wind turbine tower
5. Lengthy resultant downtime, compounded by adverse weather conditions

Anecdotal evidence obtained from a CM system manufacturer reinforces the final point, with a recent gearbox replacement resulting in over 700 hours of downtime at a wind farm owned by another UK operator (Matt Smith 2007). The physical position of these components is shown in the schematic diagram in Figure 25.

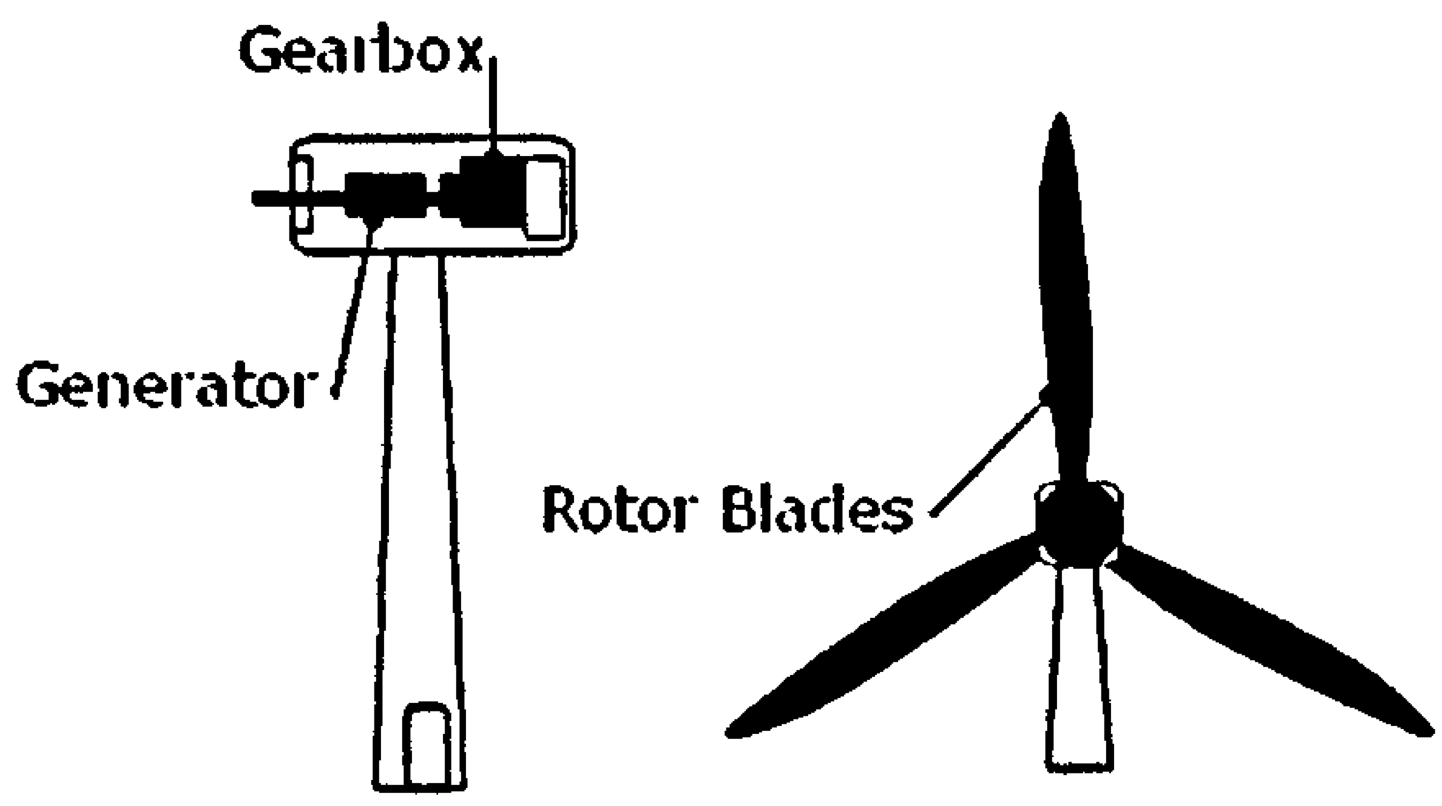

Figure 25: Schematic of Wind Turbine Components Identified by Operator

In addition to the components included because of qualitative-based recommendations of wind farm operators, it is also possible to analyse wind turbine operational data to yield some quantitative basis for identification of key WT components. Failure rates of subassemblies, and the downtime incurred for each type of failure are two indicators which are examined in the next sections. This discussion reinforces the decision on which components should be included in the Markov chain.

4.1.2 Failure Rates of Components

Section 2.1.3 illustrated one set of annual WT component failure rates from Tavner et al. (2007). Several other published studies have examined WT failure rates in detail. The data plotted in Figure 26 shows the full range of WT components and their annual probability of failure: the studies are those by Tavner et al. (2007), Ribrant & Bertling (2007), van Bussel & Zaaijer (2001) and Hahn (1999). In the case of Hahn (1999) the author provides failure rate proportions rather than absolute figures. These are used to establish the failure rates if the overall WT failure rate is 1.5 failures per annum.

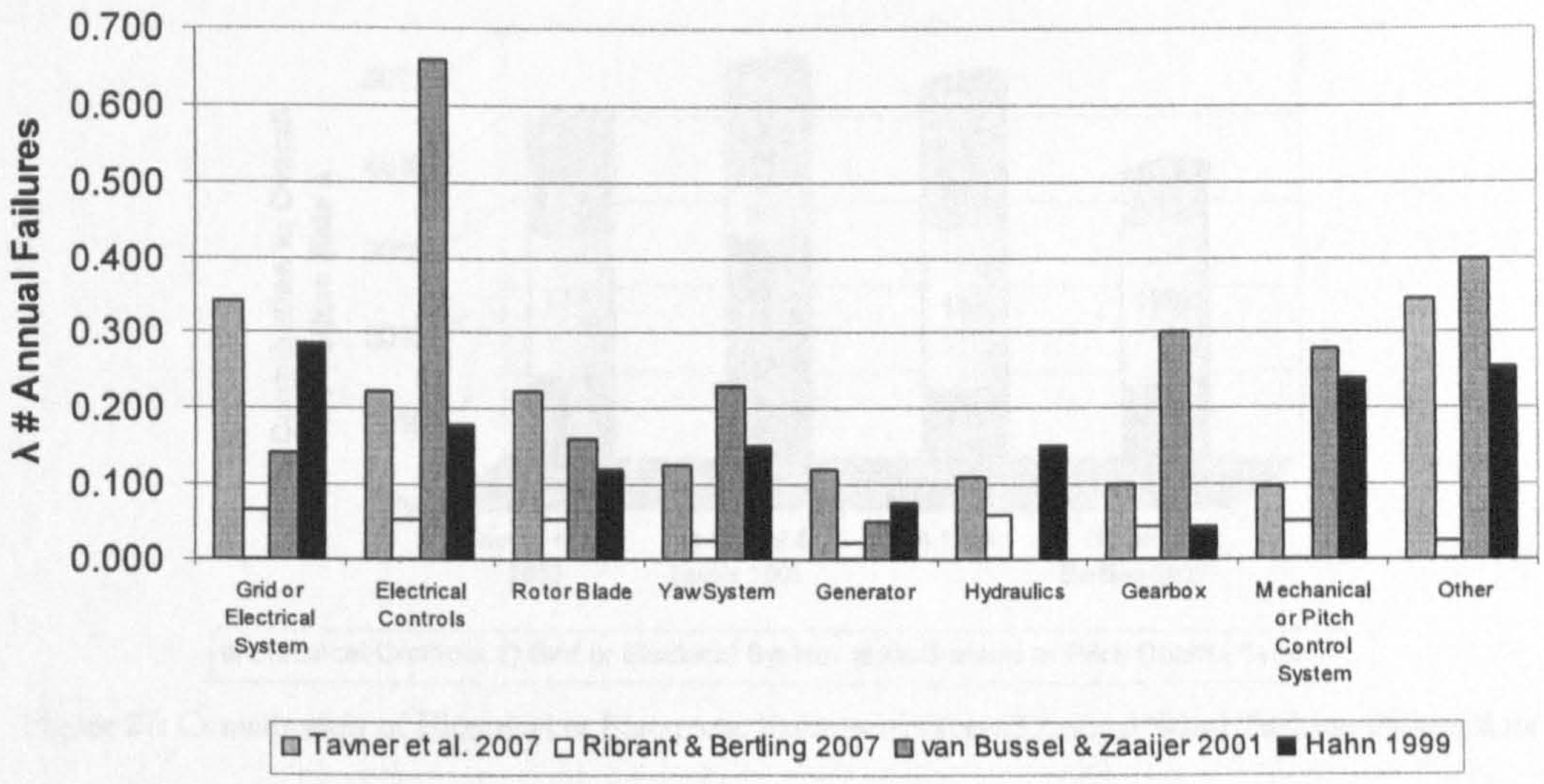

Figure 26: Comparison of WT Annual Failure Rates

The authors used contrasting methods to yield these figures: for example, Tavner, Hahn and Ribrant & Bertling all used large WT databases, while van Bussel & Zaaijer used expert judgement to quantify the sub-component probabilities. Multiple sources of data are plotted in Figure 26 to illustrate that there is no single accepted figure for sub-component failure probabilities: however there may be a range of values which represent credible approximations. This characteristic will be used later in the thesis to define a set of reliability scenarios (high, medium and low reliability) which are used to estimate the Markov transition probabilities which characterise the deterioration behaviour.

Van Bussel & Zaiijer (2001), Tavner (2007) and Holstrom & Negra (2007) all mention the high contribution of electrical-related failures to the overall WT failure rate in their papers. Indeed, if the electrical system, controls and other electrical and electronic components are amalgamated into one category, they represent 37% - 49% of all failures (see Figure 27).

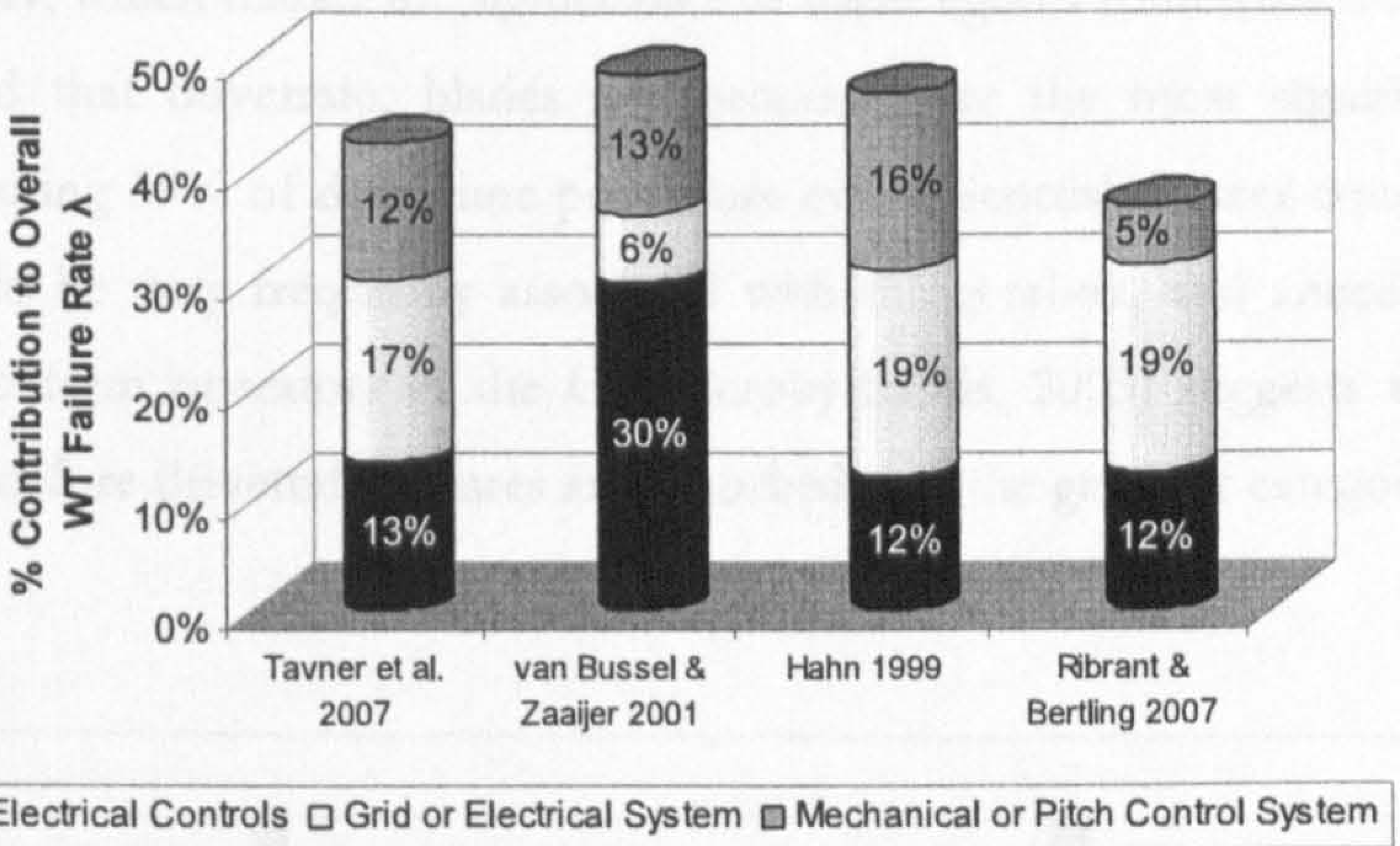

Figure 27: Contribution of Electrical & Electronic Failures to Overall Annual Wind Turbine Failure Rate

Clearly in all cases this is a significant contribution to the overall failure rate and should be captured within the failure models. It should be noted that condition monitoring of the electrical sub-systems within wind turbines is not currently practiced, although this has been suggested due to higher failure rates of electrical components in direct-drive machines (Tavner, 2005).Electrical and electronic (E&E) failures are therefore included in the model as outright failures rather than deterioration-type behaviour.

4.1.3 Impact of Component Failure – Downtime

The impact of individual component failures has been discussed in section 3.4.4 where the total outage cost (TOC) was introduced as a possible impact metric. An equivalent Table 19 can be constructed for all components if their probability of failure and typical downtime duration are known. Several estimates for the annual failure rates were shown in Figure 26, and Figure 3 showed downtime duration from a single study. To get a better understanding of downtime estimates, Figure 28 plots values from Ribrant & Bertling (2007), Windstats (2006) and an interview of Scottish Power wind farm operations staff (Yusuf Patel, 2005).

It is very interesting to note and understand the disparity between these values. The Windstats data is derived from a sample of 17,000-18,000 WTs and is therefore statistically the most credible. Conversely, over 76% of the failures reported were not classified into any particular category, which dilutes the significance of these figures somewhat. Nevertheless, it can be observed that drivetrain, blades and generator are the most significant failures, together contributing 59% of downtime per failure event. Scottish Power considered drive-train problems to be very frequently associated with the gearbox, and anecdotal evidence from other wind farm operators in the UK (Scroby Sands, 2005) suggests this is a valid assumption. Therefore drivetrain failures are absorbed into the gearbox category for the rest of this thesis.

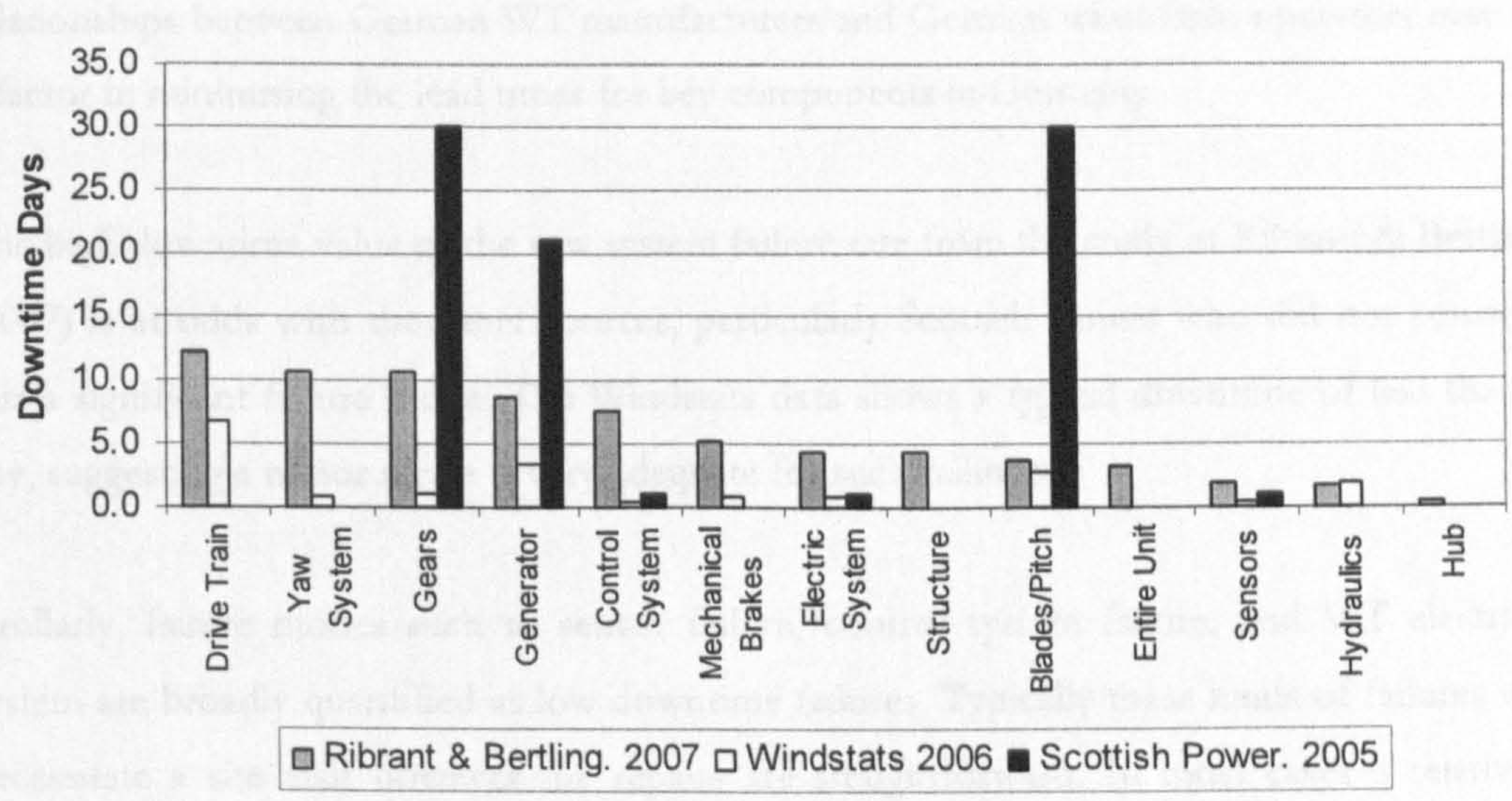

Figure 28: Downtime Estimates from 3 Sources

There is broad agreement that generator, blades and gearbox are significant failures from a downtime viewpoint, which echoes the views of Scottish Power as yielded from section 4.1.1, however the magnitude of the downtime varies considerably in Figure 28. These three key WT components are precision-engineered and tend to have extremely lengthy lead times for purchase from the manufacturer. Generally the under-capacity of wind turbine manufacturers has pushed up lead times and component costs since the turn of the century (2000-2008) (Garrad 2007). Therefore, availability of a spare has a particularly large impact on the downtime for these three key components.

Table 3 showed a range of gearbox downtime estimates, some of which were estimated based on the availability of spares. Many factors affect this lead time issue, not least the relative influence of the turbine operator. A small wind farm operator with an interest in this research had been quoted 6 months lead time (~180 days) for a replacement gearbox. The large disparity between the estimates for generator, blades and gearbox downtime in Figure 28 can be partially explained by this hypothesis, as large utilities are likely to be first in the component queue. Additionally, much of the European manufacturing base for precision-engineered WT components is in Germany, which is the source of the Windstats data plotted in Figure 28. The simplified logistics of transporting such cumbersome components within a country (i.e. no shipping is required), combined with the inevitable close relationships between German WT manufacturers and German wind farm operators may be a factor in minimising the lead times for key components in Germany.

The high downtime value of the yaw system failure rate from the study of Ribrant & Bertling (2007) is at odds with the other sources, particularly Scottish Power who did not consider this a significant failure mode. The Windstats data shows a typical downtime of less than 1 day, suggesting a minor repair is very adequate for such failures.

Similarly, failure modes such as sensor failure, control system failure, and WT electrical system are broadly quantified as low downtime failures. Typically these kinds of failures will necessitate a site visit however the repairs are straightforward. In most cases a relatively cheap electronic component repair or replacement is necessary, thus the downtime is rarely more than 1 day. The main problem with these failures is their high frequency (see Figure 26) rather than their downtime, assuming access to the site is straightforward. If access is a problem, then these trivial failures may become much more significant.

4.1.4 Impact of Component Failure – Component Cost

A set of percentages to calculate major sub-component cost from WT capital cost were proposed by Sterzinger & Svrcek (2004 p53), based on the analysis of Poore & Lettenmaier (2003 p82). These percentages were based on wind turbines rated from 500kW – 600kW. This method was used to derive component cost estimates in two published papers based on the models in this thesis (McMillan & Ault 2008, McMillan & Ault 2007) and were summarised in Table 16.

Component	Nilsson & Bertling 2007		McMillan & Ault 2007	
	£ @ 3MW	% CAPEX	£ @ 2MW	% CAPEX
Gearbox	180,000	10	100,000	8
Generator	90,000	5	50,000	4
Rotor Blade (1)	120,000	7	70,000	6
E&E Sub	7,200	0.4	5,000	0.4

Table 21: Major Component Replacement Cost Estimates – MW Class Wind Turbines

Other more recent component cost estimates differ considerably from the percentages put forward by Sterzinger & Svrcek (2004 p53). Taking figures from Nilsson & Bertling (2007) and McMillan & Ault (2007), new percentages of CAPEX have been derived (see Table 21) assuming CAPEX of £600,000 per MW. Since these are based on MW class turbines, these values may provide more accurate component costs based on percentage CAPEX. Furthermore, the percentages are in broad agreement, lending weight to these assumptions. Therefore the costs derived in McMillan & Ault (2007) are initially adopted.

Electrical and electronic-related (E&E) failures (that is sensor failure, control system failure, and WT electrical system) incur minimal repair and replacement costs. In the case of a 2MW WT, the estimated cost for a replacement was £5,000 (Yusuf Patel, 2005) which is 0.4% of CAPEX. This value is assumed to hold true for all E&E failures.

One point of interest is the relatively modest cost of replacement for a single rotor blade. In reality, all three blades in a Danish concept WT must be balanced in order that the rotor does not cause excessive and damaging vibrations to the other rotating components. Therefore when a blade fails, typically all three blades must be replaced (Yusuf Patel, 2005). The true cost of a blade failure is therefore £360,000 for a 3MW machine and £210,000 for a 2MW machine, corresponding to 21% and 18% of CAPEX respectively.

4.1.5 Applicability of Condition Monitoring Techniques

Section 2.4 discussed the CM options available, and the literature review that followed consisted primarily of monitoring systems for the rotating elements of the WT (gearboxes, generators, rotors). These are the same three key components identified by the wind farm operator: therefore the condition and deterioration characteristics of these components should be captured in the Markov model. Electrical and electronic-related failures are not currently the subject of CM and in any case tend to fail instantaneously rather than exhibiting slow deterioration behaviour. The Markov model should therefore capture the deterioration of the components in Figure 29 as well as modelling instantaneous failure of E&E components.

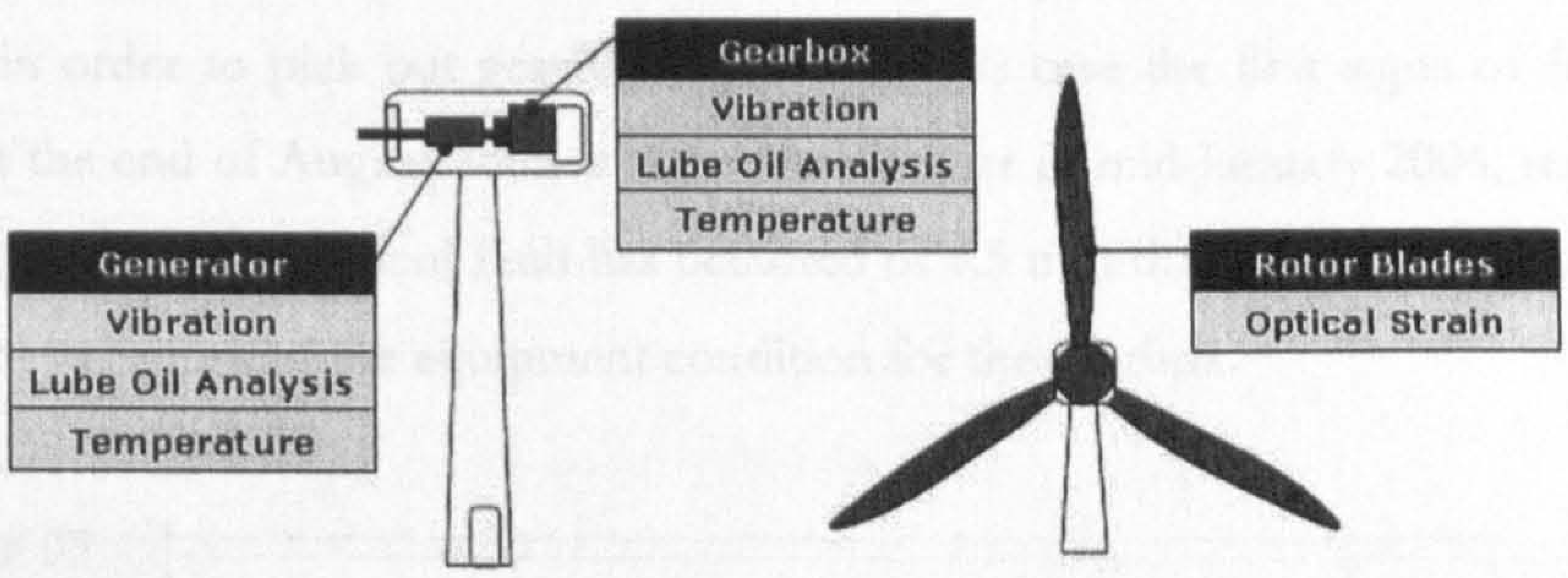

Figure 29: Condition Monitoring System for Key Wind Turbine Components

Through analysis of SCADA data it is been possible to capture specific instances of deterioration and failure which are very useful for the purposes of deciding how many states are necessary for inclusion of each component in the Markov chain. Figure 30 provides an example of the condition of the gearbox as measured via the temperature of the gearbox lubrication oil. The trace shows a region of deterioration followed by a failure: this can be thought of as corresponding to a three stage Markov deterioration model (i.e. fully up – before temperature anomaly, deteriorated – high oil temp, and failed – component outage).

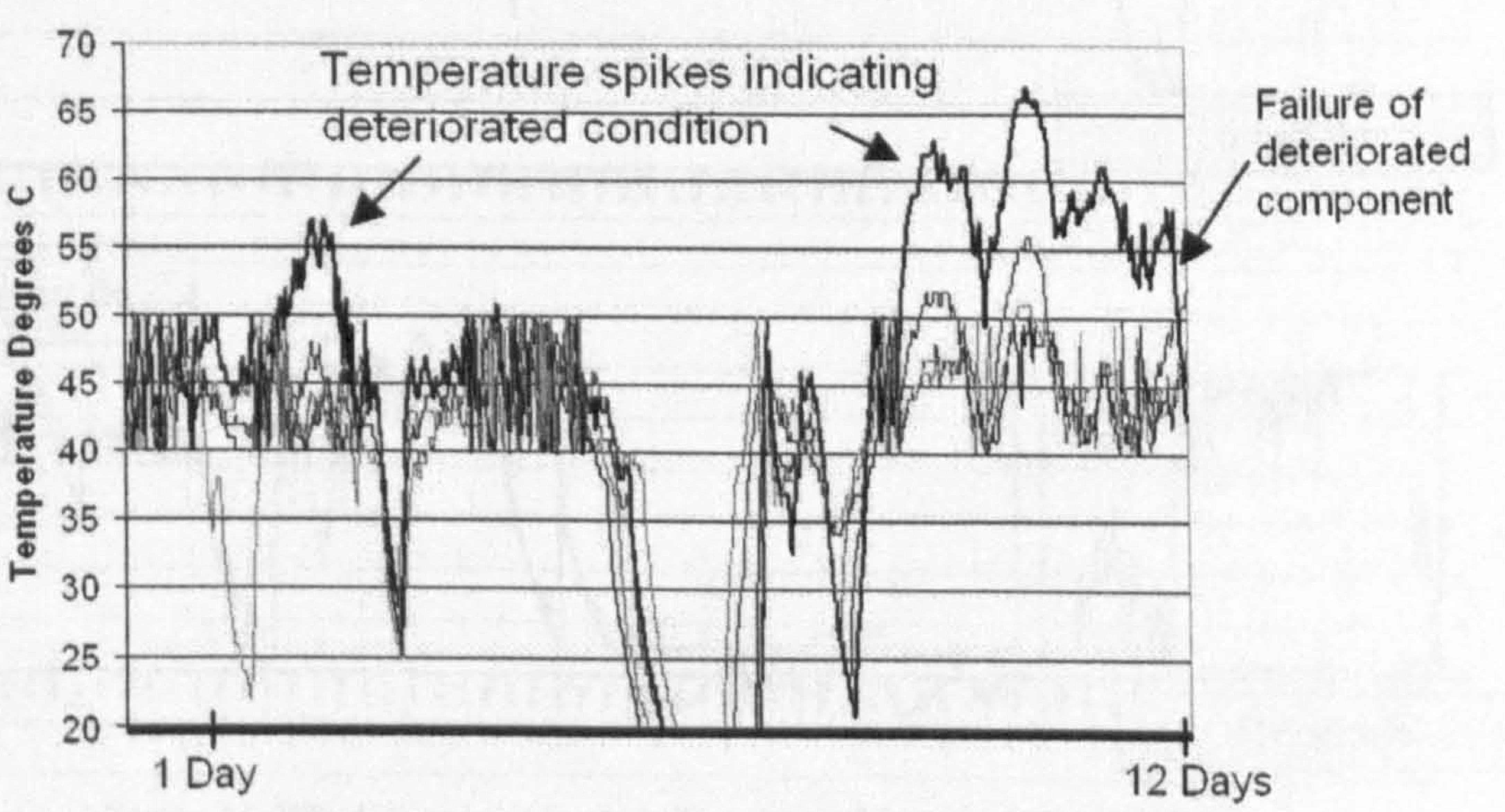

Figure 30: Gearbox Oil Condition and State Classification

In the fully up region (not shown in Figure 30, since the data for this period were unavailable), the temperature of all gearboxes in the wind farm would be broadly similar. In the deteriorated state region, the WT of interest clearly has abnormally high temperature, indicating a fault. In the failed region the temperature drops off because the components stop rotating and generating heat. It is clear that in this case three states are sufficient to represent gearbox condition. A more comprehensive view of the failure process is given in Figure 31. The gearbox oil prediction model developed by Zaher and McArthur (2007) can be applied in order to pick out gearbox failures. In this case the first signs of failure were identified at the end of August 2005 with eventual failure in mid-January 2006, resulting in a time to failure once an incipient fault has occurred of 4.5 months. Again, in this case 3 states are sufficient to represent the equipment condition for the gearbox.

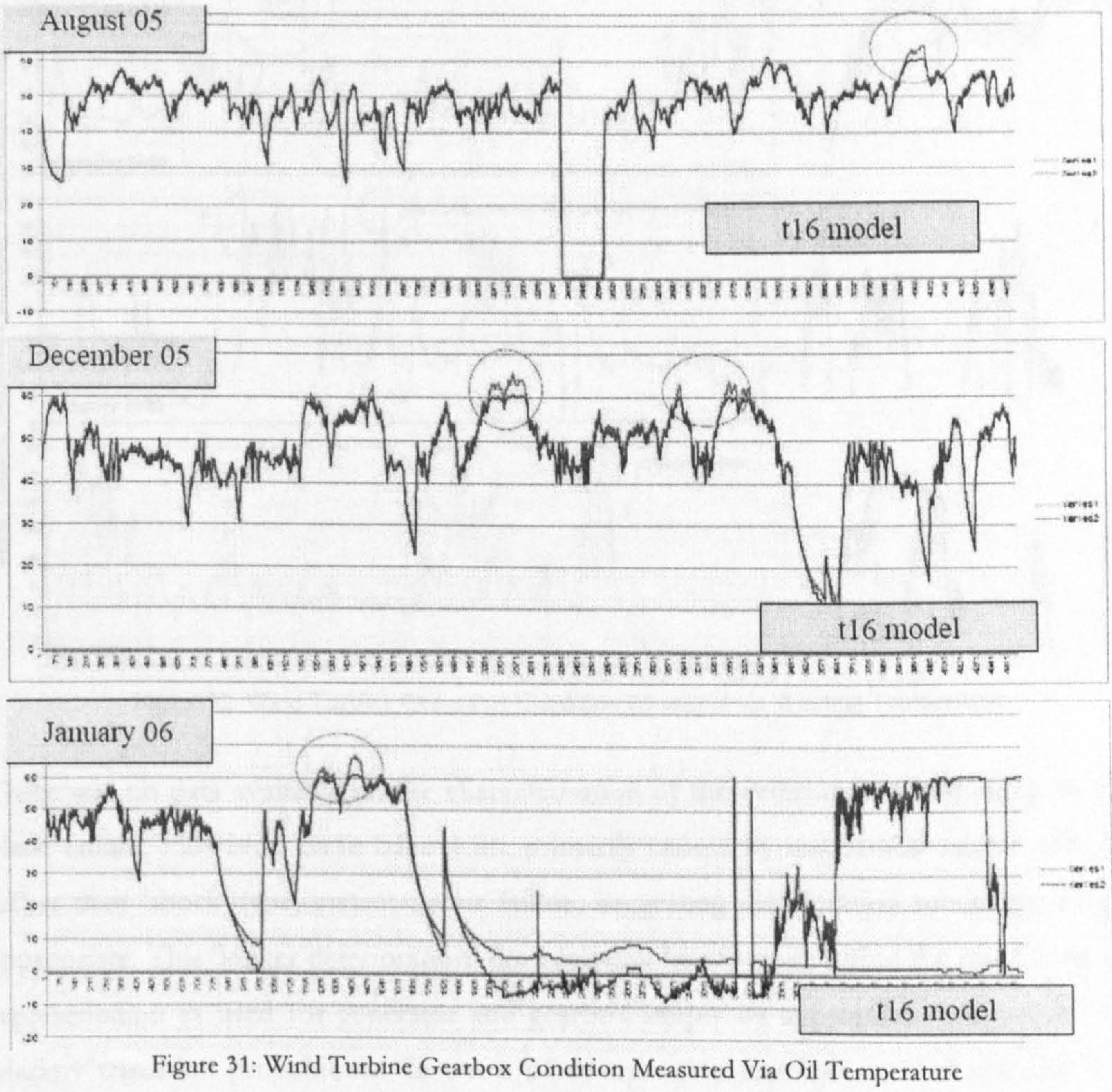

Figure 31: Wind Turbine Gearbox Condition Measured Via Oil Temperature

Another example, this time for the condition of the wind turbine generator, is shown in Figure 32. This plot shows the temperature of the generator winding which is used to gauge the health of the generator itself (the data analysis tool and prediction model were developed by Zaher (2007), but have not yet been reported in the literature). The darker trace shows higher than expected actual temperature readings, greater than those produced by the model (grey trace). Figure 32 also shows that the time to failure after the first sign of an incipient fault is approximately 7 months in this case. This is around 2-3 months longer than a gearbox failure. Further to Figure 32, the work of Anders et al. (1990) focused on generator insulation condition which was quantified using a relatively low number of states (4), therefore three states is a credible assumption.

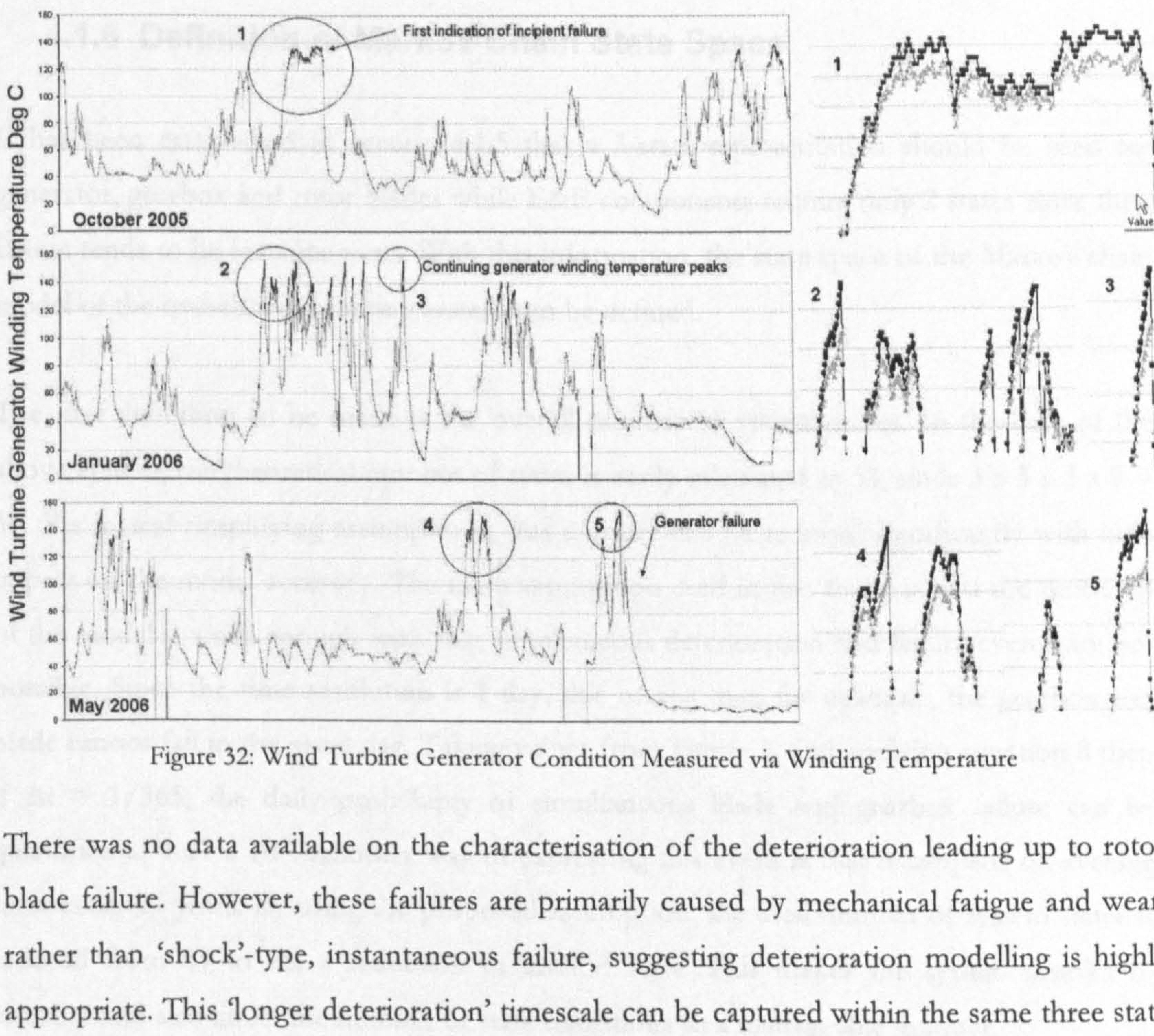

Figure 32: Wind Turbine Generator Condition Measured via Winding Temperature

There was no data available on the characterisation of the deterioration leading up to rotor blade failure. However, these failures are primarily caused by mechanical fatigue and wear, rather than 'shock'-type, instantaneous failure, suggesting deterioration modelling is highly appropriate. This 'longer deterioration' timescale can be captured within the same three state representation as used for generator and gearbox simply by appropriate estimation of the Markov transition probabilities. In terms of deterioration timeframes, Shokrieh and Rafiee

(2006) developed models to describe the deterioration process of WT blades. Their conclusions suggest that the fatigue process occurs over a timeframe of years rather than months, in contrast to the gearbox and generator. Until more detailed data on blade deterioration is available, three states can be used as a starting point for the modelling.

Finally, it must be noted that all the derived 'times to failure' and resultant probabilities are estimates based on very limited existing data and experience of WT component failures. This should be remembered when deriving maintenance policies based on these quantities. However, it is expected that more accurate estimates will be available in future, as understanding of WT component failure mechanisms is developed further.

4.1.6 Definition of Markov Chain State Space

It has been established in section 4.1.5 that a 3-state representation should be used for generator, gearbox and rotor blades while E&E components require only 2 states since their failure tends to be instantaneous. With this information, the state space of the Markov chain model of the overall wind turbine system can be defined.

The first definition to be made is the overall number of system states. In the case of the above system, the theoretical number of states is easily calculated as 54, since 3 x 3 x 3 x 2 = 54. Via logical simplifying assumptions, this number can be reduced significantly with little impact on the model accuracy. The main assumption used in this thesis is that the time step of the model is small enough such that simultaneous deterioration and failure events are not possible. Since the time resolution is 1 day, this means that, for example, the gearbox and blade cannot fail in the same day. Taking values from Figure 2, and applying equation 8 then if $\Delta t = 1/365$, the daily probability of simultaneous blade and gearbox failure can be quantified as 1.67×10^{-7}. Another way of expressing this event is that it happens on average once every 44 years. By using the proposed assumption, the total number of system states is reduced from 54 to 28, a reduction of around 48%. This makes the system simpler to visualise and also limits the number of state transitions to a manageable number.

The state transitions themselves are limited by using another assumption, that is that if the system is modelled with an intermediate state (i.e. gearbox, generator, blade) then the system must transit through this state before outright failure. This introduces some simplification error, as some of these failures will be instantaneous in nature. The main implications for the analysis in this thesis are that it will provide an optimistic appraisal of CM systems, since all failures can be detected. However, other modelling can be introduced to counter this and make the capabilities of the CM system more in line with reality. This is discussed in more detail later in the thesis (see section 5.1.9).

Taking the earlier assumption of failures modelled as absorbing states, the state space can be physically drawn. Figure 33 shows the resultant full state space, with arrows showing possible state transitions. The numbers on each large box are the state numbers i.e. 1: s_1, 2: s_2 .. 28: s_{28}. The smaller boxes correspond to the individual component condition C1 – gearbox, C2 – generator, C3 – E&E, and C4 – rotor blade. The shading of these component boxes in Figure 33 represents a stage of deterioration: fully up (white), deteriorated (grey) and failed (black).

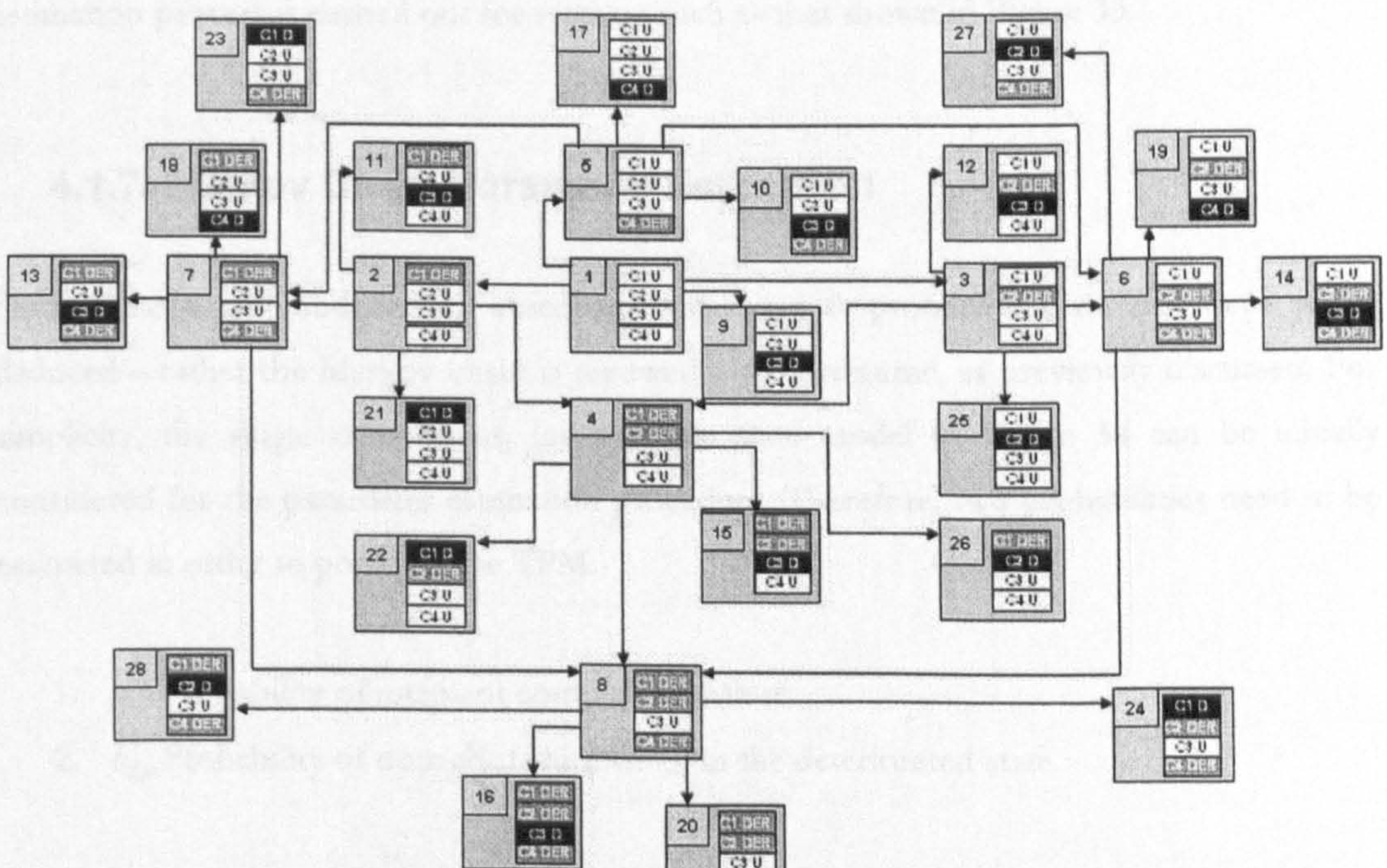

Figure 33: Wind Turbine Markov State Space - 28 States

The failure states are summarised for the system in Table 22. Since the arrows on Figure 33 show which transitions are possible, it can be clearly seen that no transitions are possible out of the failed states (9 to 28) because failures are modelled as absorbing states.

States	Component Number	From State	To State
Fully Up & Derated	C1, C2, C3, C4	1	8
E&E Failure	C3	9	16
Blade Failure	C4	17	20
Gearbox Failure	C1	21	24
Generator Failure	C2	25	28

Table 22: States and Components of Wind Turbine Markov Model

Similarly, repairs from intermediate/deteriorated states (s_2 .. s_8) are only enabled at specific times – i.e. when the maintenance interval has expired (see section 3.4.4, Figure 24). Therefore these transitions are not shown in Figure 33.

With the states and possible transitions of the Markov model defined, the next point of interest is quantification of the transition probabilities between states, often expressed as a transition probability matrix (TPM). The next section provides detail on how the parameter estimation process is carried out for systems such as that shown in Figure 33.

4.1.7 Markov Chain Parameter Estimation

Since failures are modelled as absorbing states, repair probabilities do not have to be deduced – rather the Markov chain is renewed after downtime, as previously discussed. For simplicity, the single component, intermediate state model in Figure 34 can be initially considered for the parameter estimation procedure. Therefore, two probabilities need to be estimated in order to populate the TPM:

1. $p_{1,2}$ Probability of incipient component failure
2. $p_{2,n}$ Probability of outright failure when in the deteriorated state

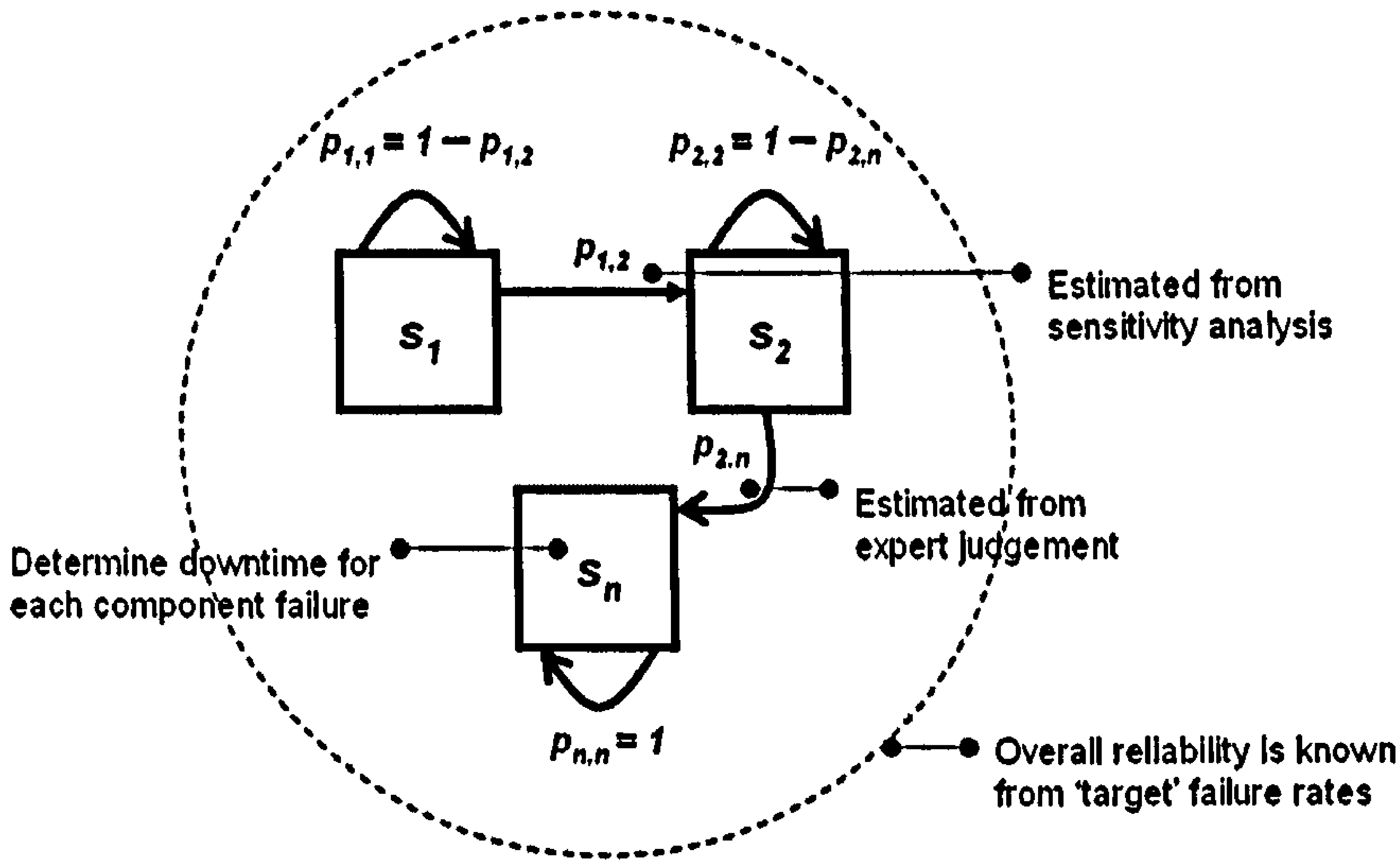

Figure 34: Simplified 3-State Markov Chain for Parameter Estimation

Estimation of $p_{2,n}$ was based on both CM data and expert opinion from industrial sources. Although the probability of failure is likely to increase the longer the component has been in a deteriorated state, at the moment insufficient data exists to implement such a (semi-Markov) model. Thus constant transition probabilities are assumed. An example of estimation of $p_{2,n}$ is based on typical time to failure of a gearbox once incipient failure has occurred, which has been quantified by a CM expert as 4 months (Matt Smith, 2006). The SCADA data analysis presented earlier in Figure 31 broadly agrees with this value (4.5 months), and represents the best estimation possible, due to a lack of extensive research on this subject. Based on this information, the equivalent daily probability can be calculated as $1/120^{th}$ of this 4 month figure since the probability is proportional to the size of time step being evaluated, assuming a constant failure rate (see equation 8 in section 3.2.1).The remaining probability of incipient failure $p_{1,2}$ is deduced by conducting a simple 6-step sensitivity analysis procedure, which is detailed below.

1. Estimate $p_{2,n}$ from expert judgement, downtime for s_n and decide target failure rates

The probability of outright failure can be estimated from expert judgement in the absence of suitable data (as proposed by Backlund and Hannu, 2002). Downtime estimates can be derived from the literature outlined in section 4.1.3, Figure 28. Similarly, failure rates have been measured and published (see section 4.1.2, Figure 26).

2. Read in new incremental guess for unknown parameter $p_{1,2}$

Begin first iteration at default value of 1 x 10^{-4}. Otherwise revise up or down depending on result of last simulation output.

3. Run simulation until steady-state value is reached

The more states the system has, the more MCS trials will be necessary so that the least likely transitions and associated events occur at least once during the simulation period.

4. Inspect result for annual component reliability – revise $p_{1,2}$ up or down to match

When the simulated annual failure rate is obtained, it is compared to the target failure rate. If the target failure rate has been under-estimated, $p_{1,2}$ is revised upwards. If the target failure rate has been over-estimated, $p_{1,2}$ is revised downwards.

5. Repeat steps 2-4 until MCS output adequately matches chosen 'target' failure rates

The process is repeated, with adjustments to the Markov transition probabilities (equivalent to $p_{1,2}$) up and down as necessary. The process stops when all MCS-generated failure rates are within an acceptable degree of accuracy (confidence limit) as compared with target values. Definition of the confidence limit is described in section 4.1.8.

6. Choose this value of $p_{1,2}$ which results in best fit to chosen failure rates

This TPM value (equivalent to $p_{1,2}$) is used for subsequent experimentation using the Markov model as part of techno-economic evaluation of WT CM.

End Sensitivity Analysis

It should be noted that the output metrics produced by the simulation also depend on the assumed maintenance policy and any applied constraints. For the model fitting procedure, this meant that 6-monthly TBM was adopted for the base case.

Assumptions regarding downtime have a significant effect on other metrics generated such as annual failure rate of components, even if the TPM has not changed. The reason for this is that the downtime is being used instead of a repair rate in the model. A system with relatively small downtime has more time spent in the up states (s_1 and s_2 in the case of Figure 34). This means that the systems 'exposure' time to potential failures is relatively high. On the other hand a system with long downtime has a shorter time during which it is operating and has less exposure to failure. The result is that if the Markov TPM is fitted assuming small downtimes, and then the downtimes are adjusted upwards, this will have the effect of reducing the component failure rates, because the total time the system is exposed to failure has reduced, even though the transition probabilities have not been altered. This is roughly equivalent to the theory behind equation 8 earlier in the thesis.

4.1.8 Calculation of Confidence Limit

The degree of MCS accuracy mentioned earlier is determined by calculating the confidence limits (L) of the four individual component failure rates, and using this as a measure of how well the simulation fits real values. More generally, the confidence limit is a measure of the statistical confidence in the quantity: it is related to the variance, the number of samples taken and also to the assumed distribution of samples.

Often in statistical analysis it is assumed that the sample is normally (Gaussian) distributed. However, the most suitable probability distribution to evaluate the level of confidence for relatively small numbers of samples (e.g. <30) is the student-t distribution. The relevant equations for the student-t probability density function (PDF) are explored in Appendix B.

In the case of this work, the overall output from each simulation constitutes one sample – since 30 samples are taken, the student-t distribution for 29 degrees of freedom is adopted (degrees of freedom = N-1). The probability density function of the student-t distribution for 29 degrees of freedom is plotted in Figure 35.

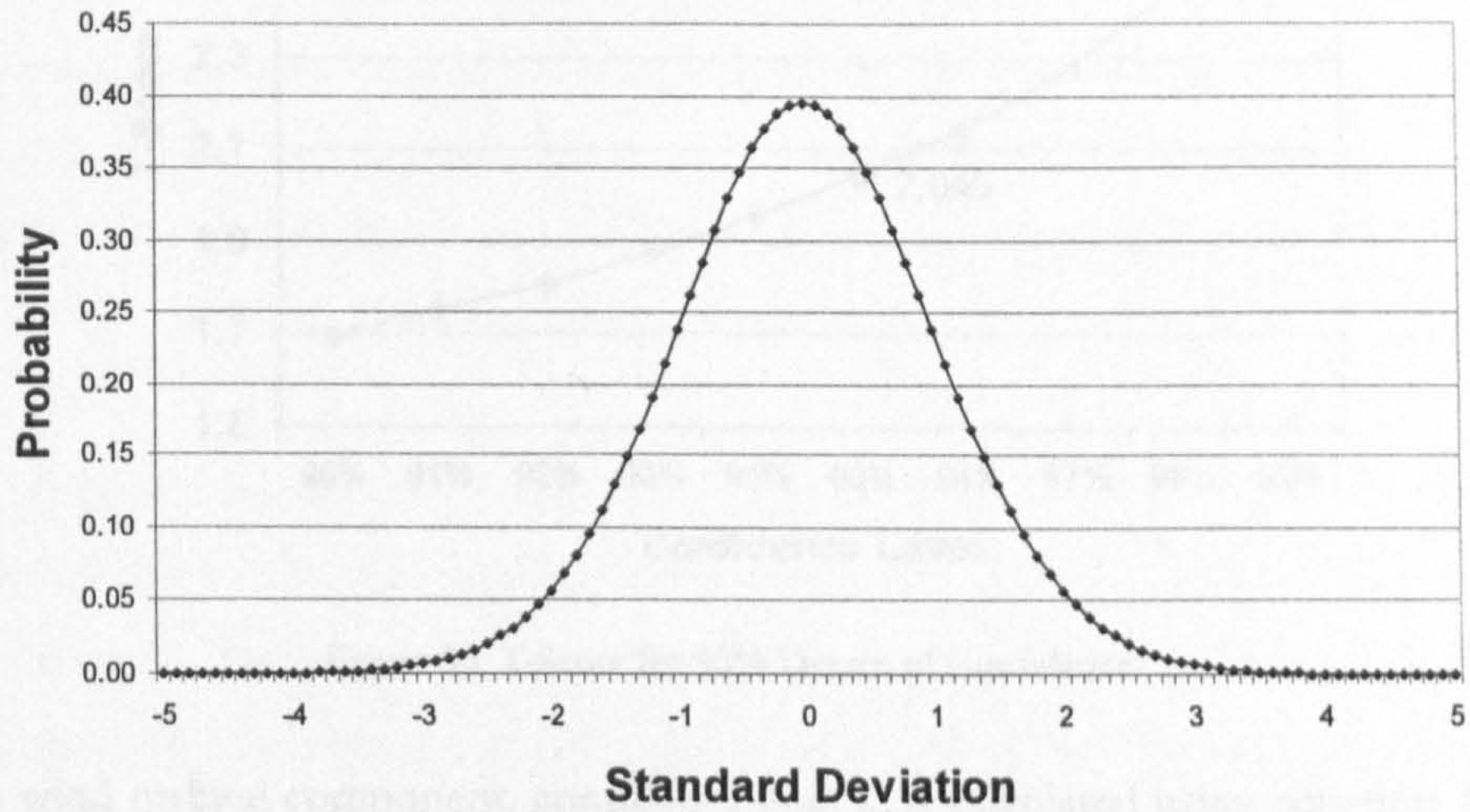

Figure 35: Student-t Probability Density Function for 29 Degrees of Freedom

The modeller sets the degree of confidence (i.e. 0-100% confidence) and a t-score equivalent (corresponding to the standard deviation) for this degree of confidence is used to calculate the confidence limit. An example of this is shown in Figure 36, where confidence levels of 90-99% are plotted in relation to their student-t scores. The t-scores correspond to the number of standard deviations from the mean of a probability distribution with two tails (i.e. the quantity can be under- or over-estimated). Figure 36 shows that for 95% confidence, the t-score is 2.045.

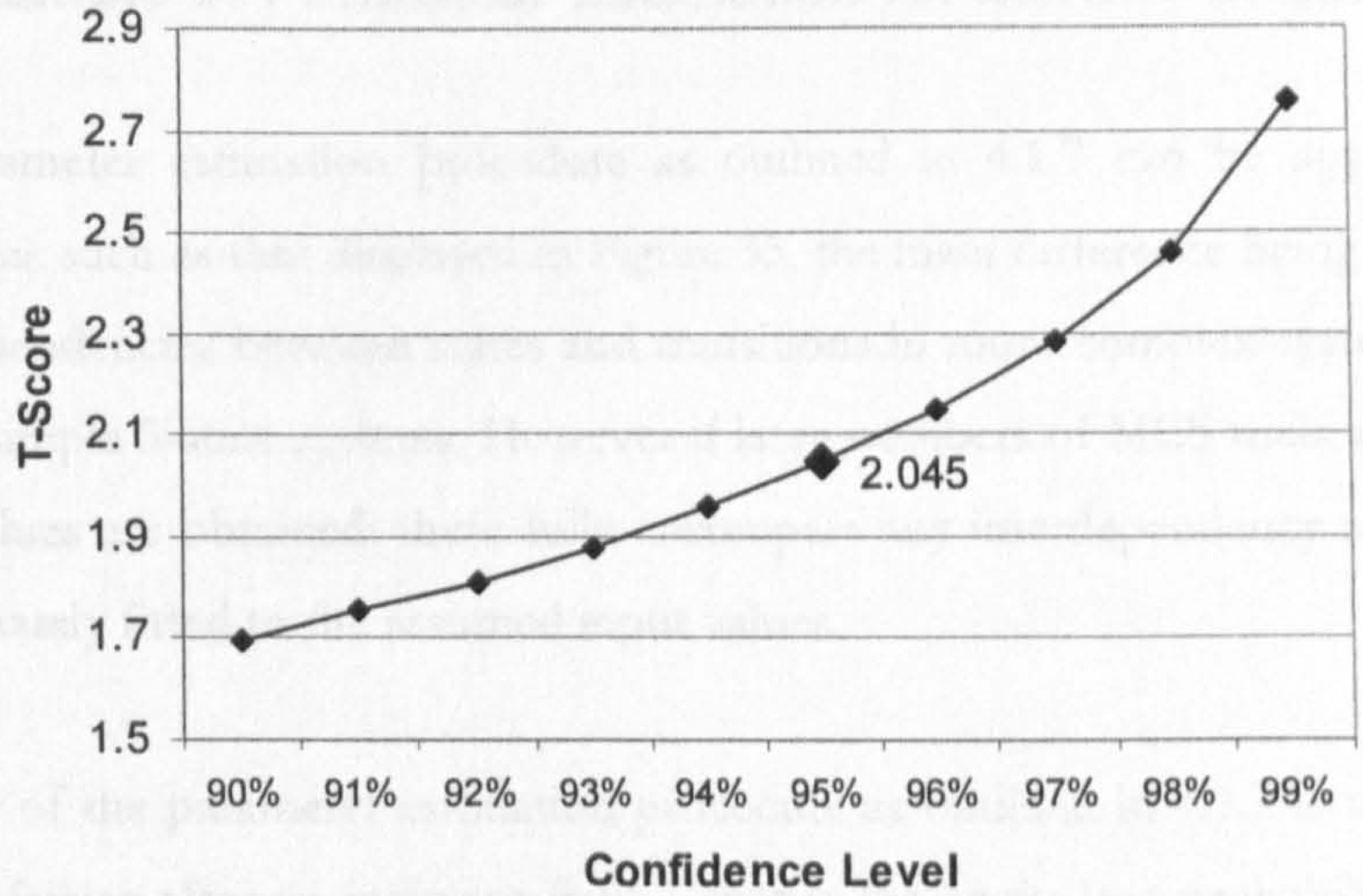

Figure 36: T-Score for 95% Degree of Confidence

For each wind turbine component, confidence limit L is calculated using equation 39 where 2.045 is the t-score of the student-t distribution with 29 degrees of freedom, $\sigma_{\lambda CMP}$ is the standard deviation of the annual sub-component failure rate and N is the number of samples. The steady-state values (step 3 in sensitivity analysis) are reached by conducting a large number of MCS trials. This number was 364 (approx. days in year) x 20 (WT operation years) x 2 (extra factor to increase likelihood of extreme events) = 14,560. The MCS was repeated 30 times to reduce the uncertainty so the total number of trials = 14,560 x 30 = 436,800. Based on this analysis, an example calculation is shown in Table 23. The final column, L, is the calculated confidence limit for the individual component failure rate estimates.

$$L = \pm \frac{2.045 \times \sigma_{\lambda CMP}}{\sqrt{N}} \tag{39}$$

Component	Annual Failure Rate λ	Standard Deviation σ	Confidence Limit L
Gearbox	0.096	0.056	0.021
Generator	0.129	0.038	0.014
Rotor Blade	0.203	0.073	0.027
E&E	0.638	0.114	0.043

Table 23: Calculation of Error Bounds Based on 95% Confidence Limits

4.1.9 Example of Parameter Estimation for Markov Chain

The same parameter estimation procedure as outlined in 4.1.7 can be applied to more complex systems such as that displayed in Figure 33, the main difference being that there are some inter-dependencies between states and transitions in more complex systems which do not appear in simple 3-state systems. However if large numbers of MCS trials are conducted, steady-state values are obtained: these fully encompass any interdependency and ensure the model is adequately fitted to the assumed input values.

The first stage of the parameter estimation procedure as outlined in 4.1.7 is to estimate the probability of failure after an incipient fault – that is the equivalent probabilities of $p_{2,n}$ for the fully defined Markov model of the wind turbine system. In practice this is the most difficult parameter to estimate, because it often has to be based on expert knowledge due to a lack of WT component deterioration data (e.g. there was no blade deterioration data available for use in this thesis). Nevertheless, using a mixture of domain knowledge and data, a set of estimates of these quantities for different components can be produced. These are shown in Table 24.

Component	Time to Failure after Incipient Fault Months	Probabilities from Figure 33 Equivalent to $p_{2,n}$	Approx. Probability 1 day resolution
Gearbox	4*	$p_{2,21}\ p_{4,22}\ p_{7,23}\ p_{8,24}$	0.00857
Generator	6**	$p_{3,25}\ p_{4,26}\ p_{6,27}\ p_{8,28}$	0.00571
Rotor Blade	24***	$p_{5,17}\ p_{6,19}\ p_{7,18}\ p_{8,20}$	0.00143

Table 24: Estimation of Probability of Failure after Occurrence of Incipient Fault.

With respect to the 'time to failure after incipient fault' for each component in Table 24, the 4* month figure for the gearbox was derived from expert judgement (Matt Smith, 2006) and this value was reinforced by the CM data presented in Figure 31. The 6** month figure for the generator was derived from inspection of SCADA records, where Figure 32 (CM trace for generator winding temperature) suggested a 'time to failure after incipient fault' of 2-3 months more than the gearbox. Finally, the figure of 24*** months for the rotor blade was derived from the assumption that structural fatigue is a relatively slowly developing failure mode relative to the equivalent time for the generator and gearbox. Studies have shown that blade deterioration occurs over years rather than months (see Shokrieh and Rafiee (2006)).

The early warning capabilities of rotor blade CM are not yet well known, however for the analysis in this thesis it is assumed that deterioration can be detected adequately.

The first stage of the parameter estimation procedure as outlined in 4.1.7 also required downtimes and target failure rates to be specified. The downtime durations for replacement are taken as the 'Scottish Power 2005' estimates from Figure 28 – TBM is applied on a 6-monthly basis, the effect of which is to restore the WT to the fully up condition ('good as new' maintenance). For this example, the target probabilities for the individual annual component failure rates are taken from Tavner et al. (2007), which has been presented earlier in the thesis. They are summarised in Figure 37, thus completing step one of the parameter estimation procedure.

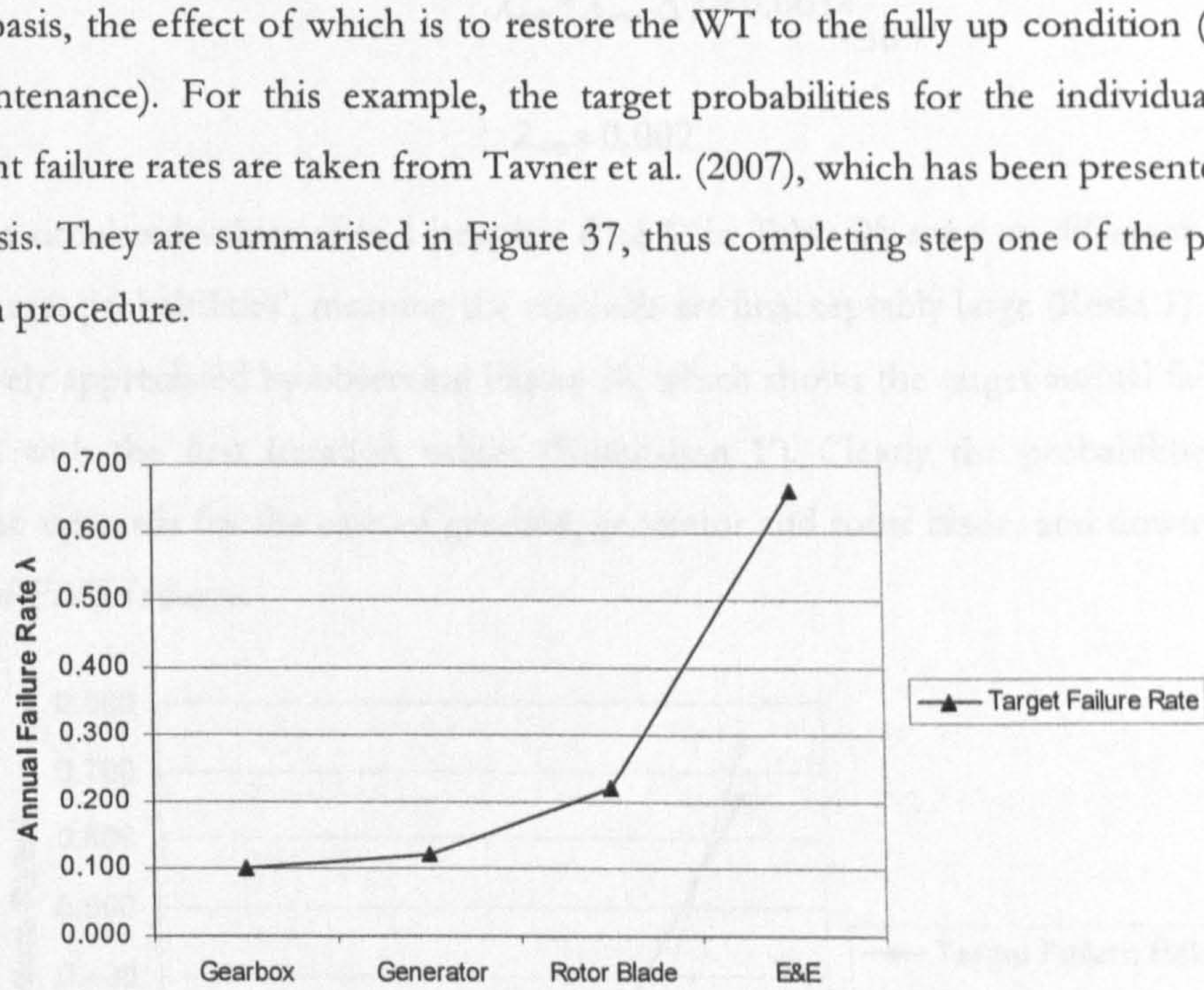

Figure 37: Annual Failure Rates (Target Probabilities) for Markov WT Component Deterioration Model

The second step of the parameter estimation procedure is to read in a new value for the probability of incipient failure. Initial guesses are shown in Table 25 along with the result of the first simulation output (Iter 1). The Resid 1 column contains the risiduals: that is the difference between the target probability and the simulated value (iter 1 in this case).

Transition Probability	Component	TPM Value	Target Probability	Iter 1	Resid 1
PR 1-2, 3-4, 5-7	Gearbox	0.000100	0.100	0.015	-0.085
PR 1-3, 2-4, 5-6	Generator	0.000100	0.120	0.018	-0.102
PR 1-5, 2-7, 3-6, 4-8	Blade	0.000100	0.223	0.003	-0.221
1-9, 2-11, 3-12, 4-15, 5-10, 6-14, 7-13, 8-16	E&E	0.002000	0.661	0.734	0.073

Table 25: First Pass of TPM Parameter Estimation Procedure

The reason that the E&E TPM values are different from the other initial guesses is that, since there is no intermediate state for E&E components, the failure probability can be roughly estimated directly from the annual rate, as shown below.

$$\lambda_{annual} = 0.661 \quad \text{(See Figure 37)}$$

$$\lambda_{daily} = \lambda_{annual} \Delta t = 0.661 \times \frac{1}{365} \quad \text{(See equation 7, 3.2.1)}$$

$$\therefore \lambda_{daily} \approx 0.002$$

Clearly the simulated values after 1 iteration (Iter 1) in Table 25 are very different from the desired 'target probabilities', meaning the residuals are unacceptably large (Resid 1). This can be intuitively appreciated by observing Figure 38, which shows the target annual failure rates compared with the first iteration values ('Simulation 1'). Clearly the probabilities require adjustment: upwards for the case of gearbox, generator and rotor blade, and downwards for the case of E&E failures.

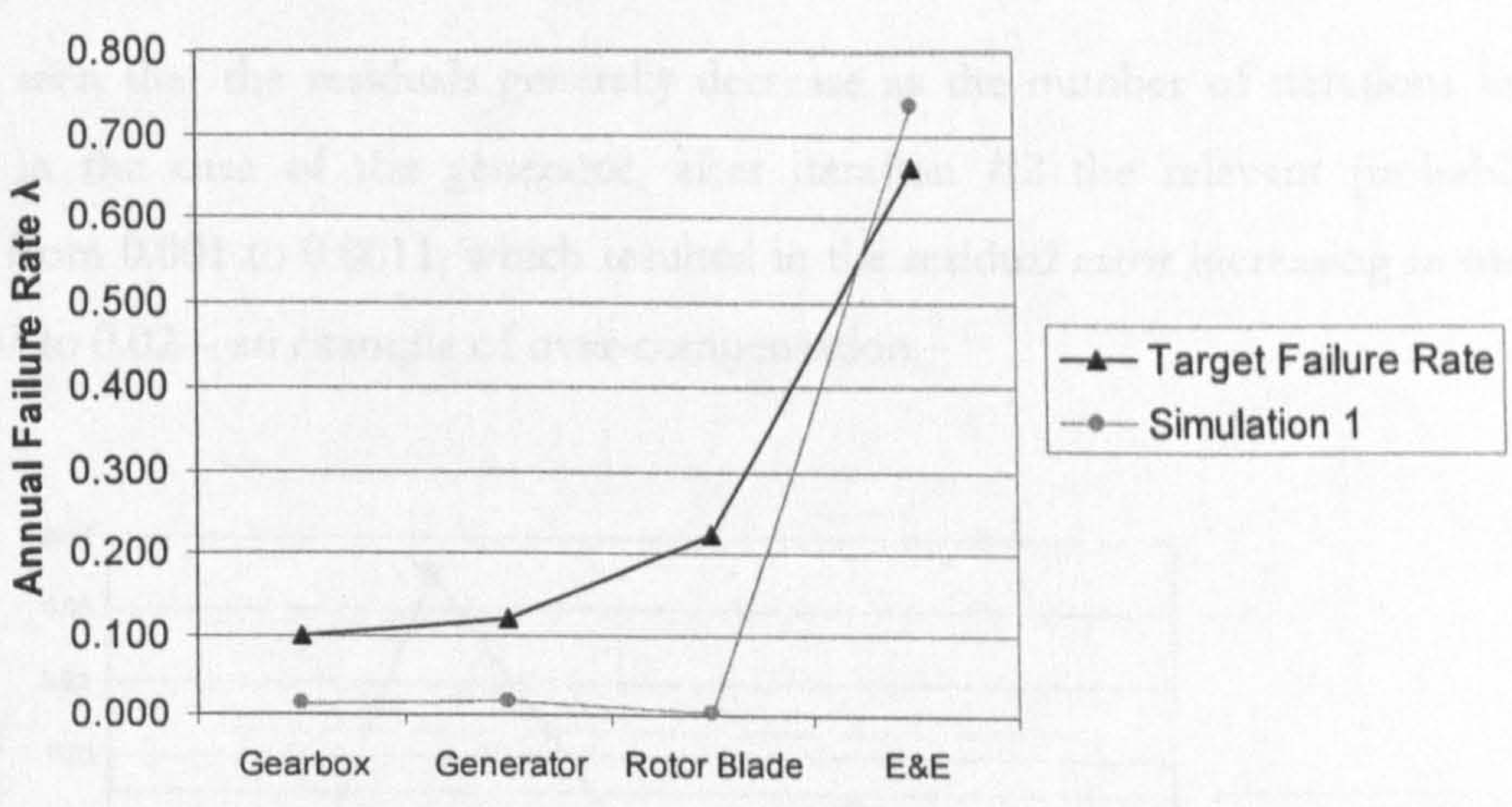

Figure 38: Target Annual Failure Rate and Simulated Failure Rate after 1 Iteration

The TPM values are therefore adjusted according to Table 26, corresponding to step 4 in the sensitivity analysis procedure. The iterative process continues until the difference between the simulated values and target probability are within the simulation confidence limits. Since the adjustment of the TPM values is essentially a manual process, the number of iterations needed to do this varies depending on the judgement of the modeller. For example, in the case of Figure 38 the rotor blade was the least accurate of the failure rates. So the action taken in Table 26 is to multiply the transition probability by 50.

Target Probability	Iteration 1	Residual 1	Action on Transition Probability	New TPM Value
0.100	0.015	-0.085	X 10	0.001
0.120	0.018	-0.102	X 10	0.001
0.223	0.003	-0.221	X 50	0.005
0.661	0.734	0.073	X 0.90034	0.00180068

Table 26: Adjustment of TPM Values after single Iteration

For this case, 5 iterations were sufficient to estimate the TPM parameters with accuracy determined by the confidence limits. These limits are constant because the number of MCS trials is constant for each iteration. The residual error should decrease as the number of iterations increases, unless the modeller over-compensates by over- or under- estimating the change to the TPM: this can clearly be seen in the plots of the residuals over 5 simulation iterations shown for gearbox (Figure 39), generator (Figure 40), rotor blade (Figure 41) and E&E failure (Figure 42).

It can be seen that the residuals generally decrease as the number of iterations increases. However in the case of the generator, after iteration #2 the relevant probability was increased from 0.001 to 0.0011, which resulted in the residual error increasing in magnitude from 0.007 to 0.02 – an example of over-compensation.

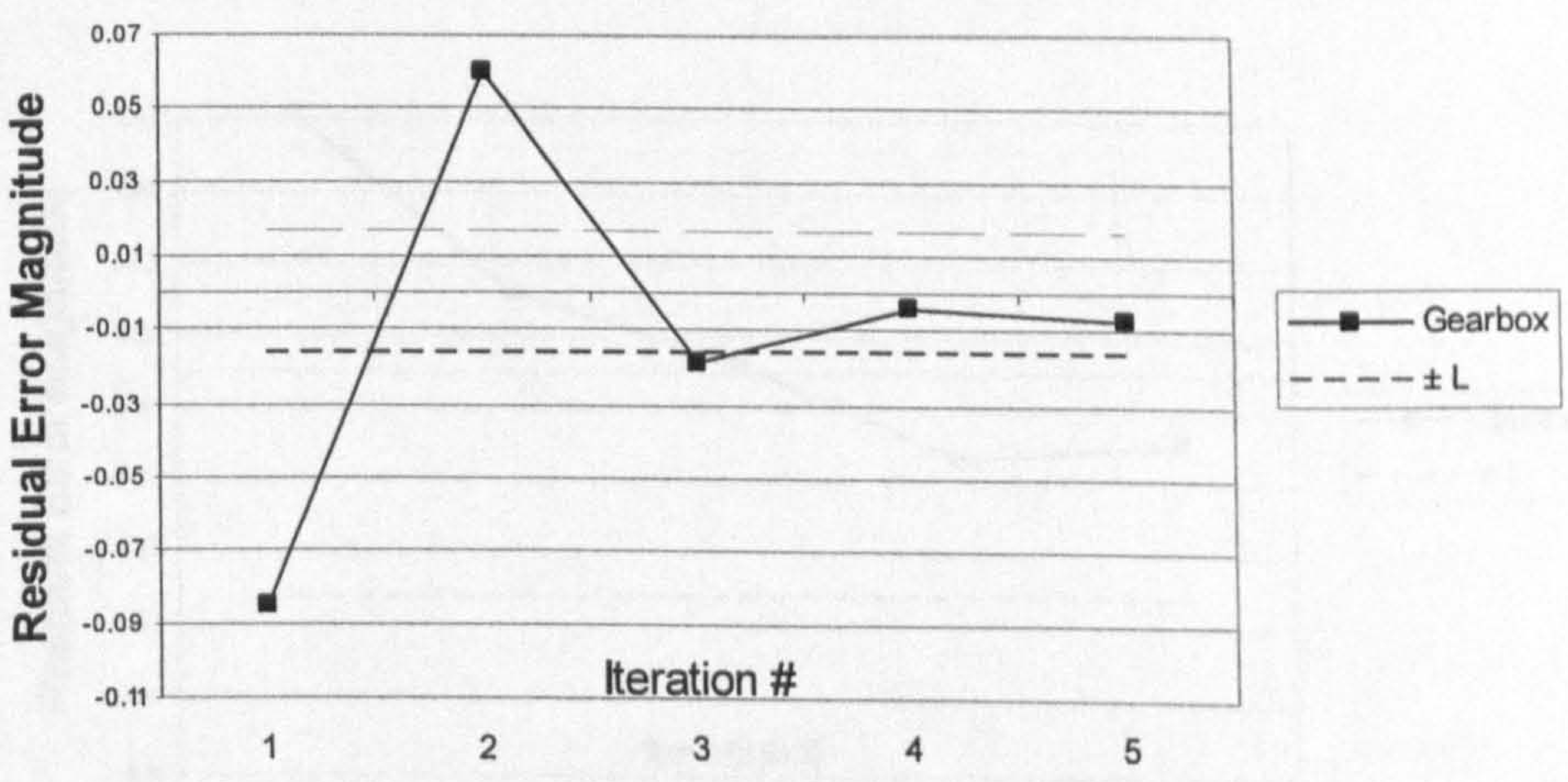

Figure 39: Residuals for Markov TPM Parameter Estimation of Gearbox

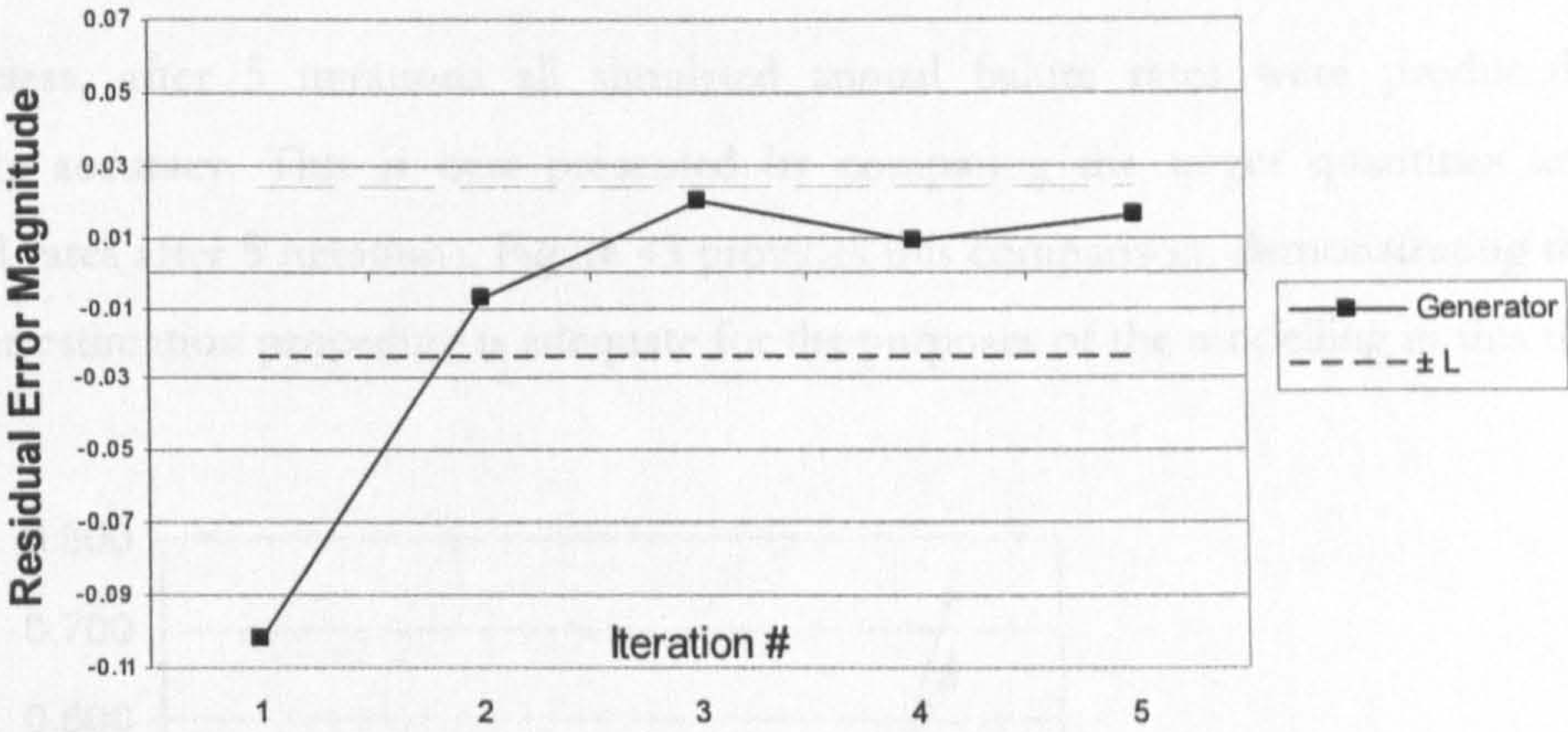

Figure 40: Residuals for Markov TPM Parameter Estimation of Generator

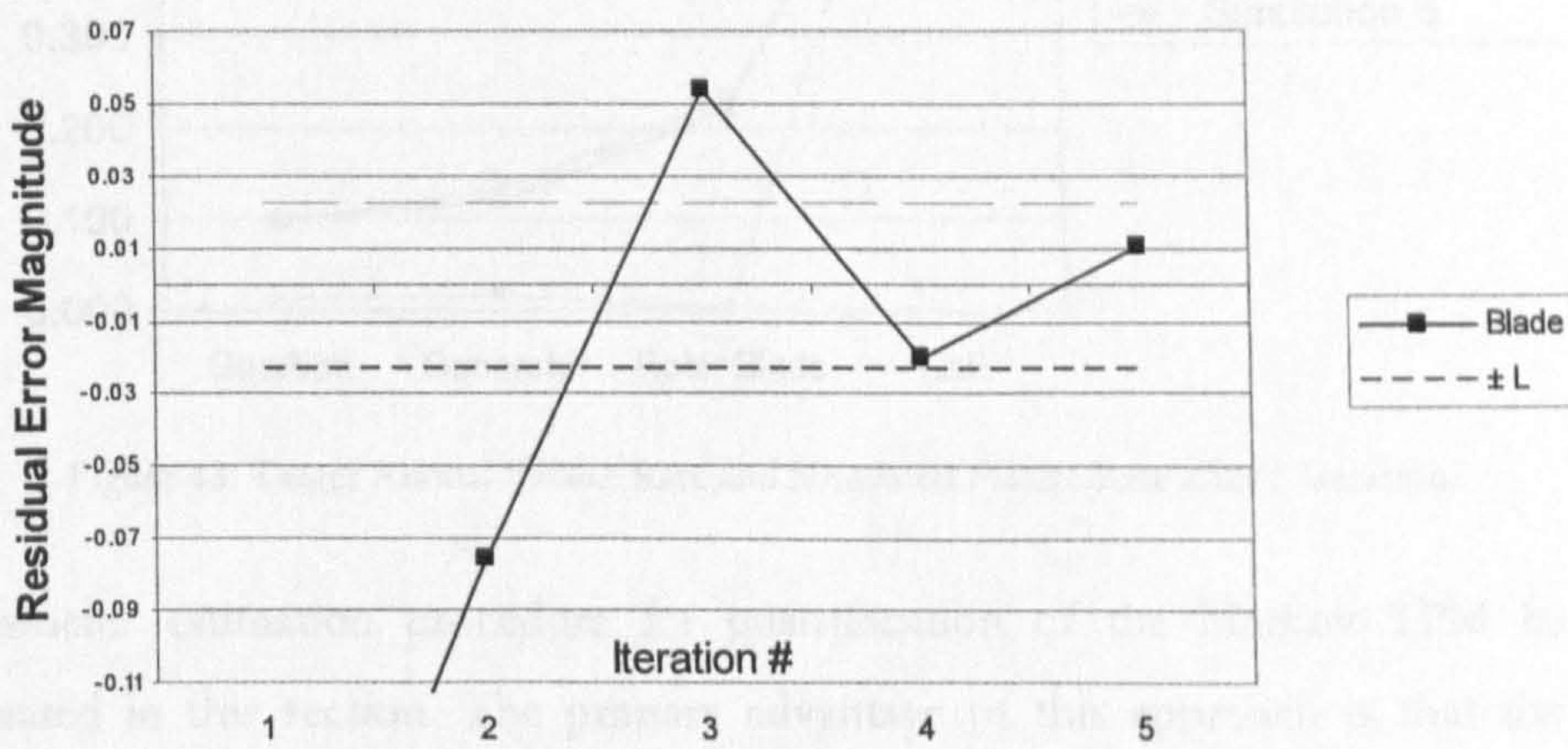

Figure 41: Residuals for Markov TPM Parameter Estimation of Rotor Blade

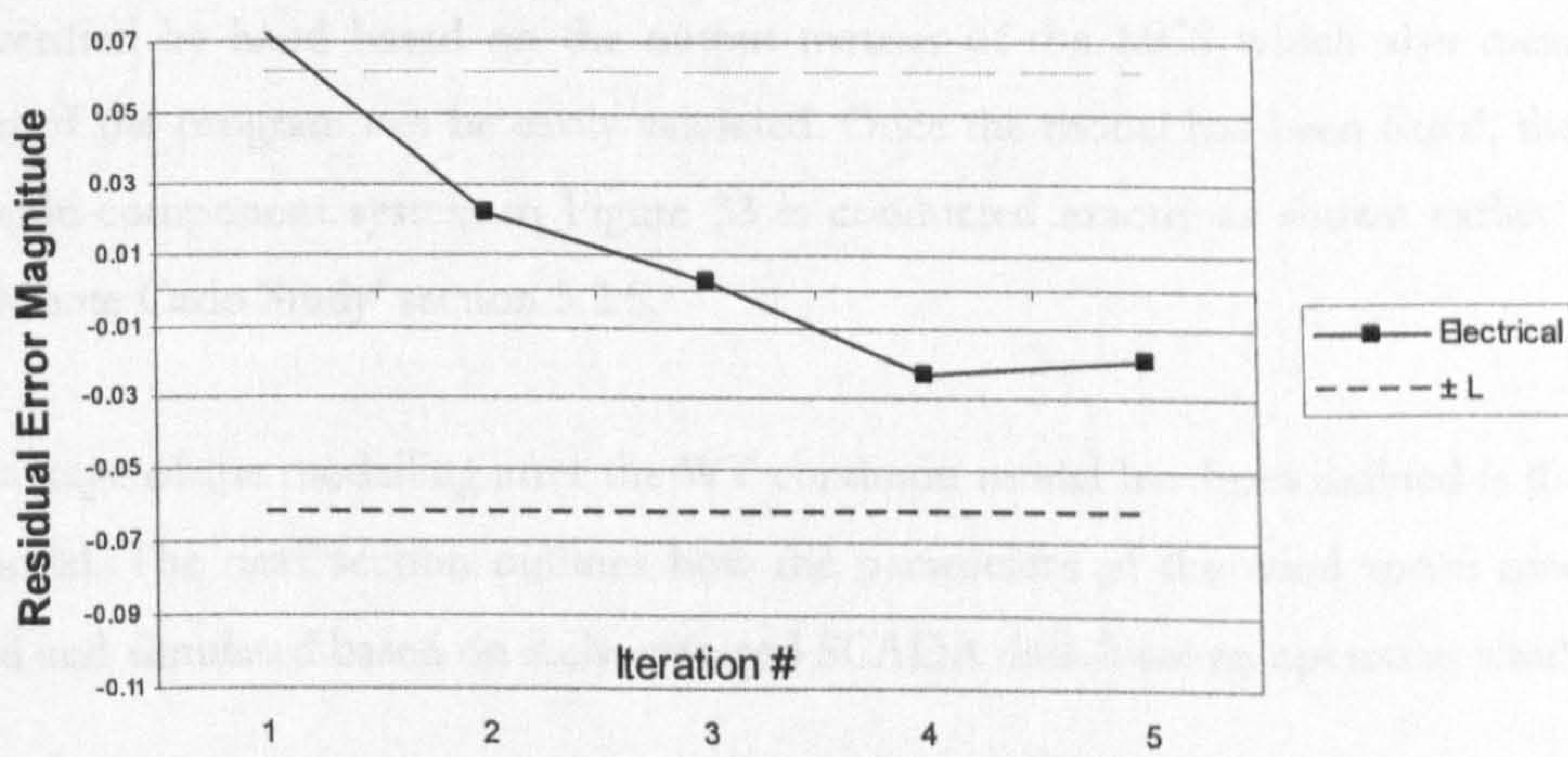

Figure 42: Residuals for Markov TPM Parameter Estimation of Electronic & Electrical Failure

Nevertheless, after 5 iterations all simulated annual failure rates were produced with acceptable accuracy. This is best presented by comparing the target quantities and the simulated rates after 5 iterations. Figure 43 provides this comparison, demonstrating that the parameter estimation procedure is adequate for the purposes of the modelling in this thesis.

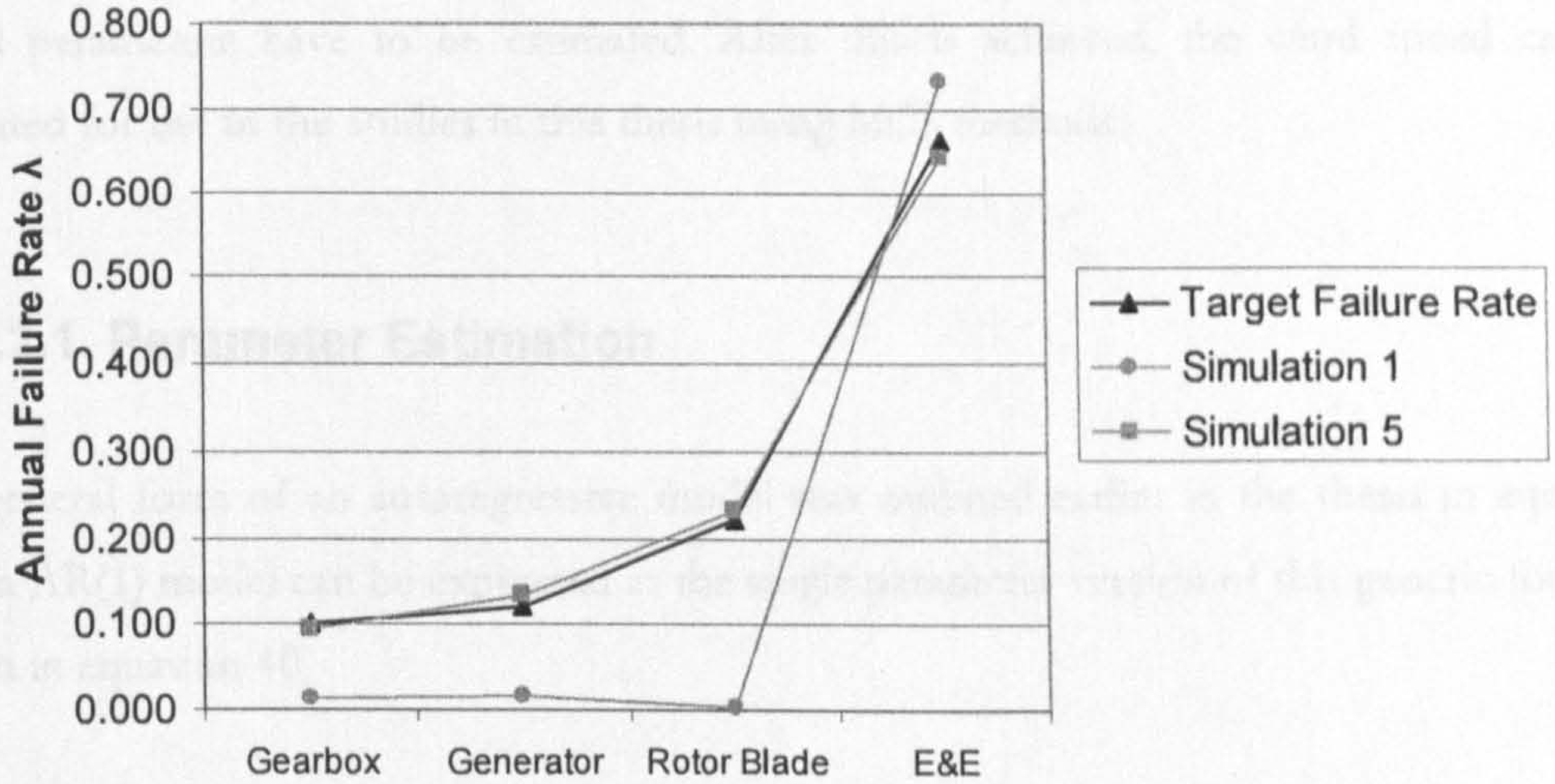

Figure 43: Target Annual Failure Rate and Simulated Failure Rate after 5 Iterations

The parameter estimation procedure for quantification of the Markov TPM has been demonstrated in this section. The primary advantage of this approach is that the model outputs can be validated using the known overall component reliability figures as well as other known metrics such as typical WT availability. Additionally, much of the calculation can be verified by hand based on the output metrics of the MCS which also means the operation of the program can be easily validated. Once the model has been fitted, the MCS of the multi-component system in Figure 33 is conducted exactly as shown earlier in the 'Simple Monte Carlo Study' section 3.2.5.

The next stage of the modelling after the WT condition model has been defined is the wind speed model. The next section outlines how the parameters of the wind speed model are estimated and simulated based on daily averaged SCADA data from an operating wind farm.

4.2 Defining a SCADA Data Based Wind Speed Model

The single parameter autoregressive (AR(1)) model has been established as the wind speed model for use in this thesis, as defined in section 3.3. Heuristic rules were used to classify the model based on the ACF and PACF functions, assuming a time step of 1 day (i.e. 10 minute SCADA data is averaged over this period). Once the model has been classified as AR(1), the model parameters have to be estimated. After this is achieved, the wind speed can be simulated for use in the studies in this thesis using MCS methods.

4.2.1 Parameter Estimation

The general form of an autoregressive model was outlined earlier in the thesis in equation 25. An AR(1) model can be expressed as the single parameter version of this generic form, as shown in equation 40.

$$z_t - \mu = \phi_1 (z_{t-1} - \mu) + a_t \tag{40}$$

Therefore, four parameters in total are required to characterise the wind speed.

1. Mean of series, μ_z (see equation 28)
2. Variance series, σ_z^2 (see equation 29)
3. AR model parameter ϕ_1
4. Variance, σ_a^2 of Gaussian 'white' noise term a_t

The 'white' noise or error (a_t) associated with the AR process is modelled via a Gaussian (also known as 'normal') probability density function (PDF) with zero mean. This function is plotted in Figure 44 for various values of standard deviation. The standard deviation of a_t (σ_a^2) and autoregressive parameter ϕ_1 are estimated using ordinary least squares (OLS).

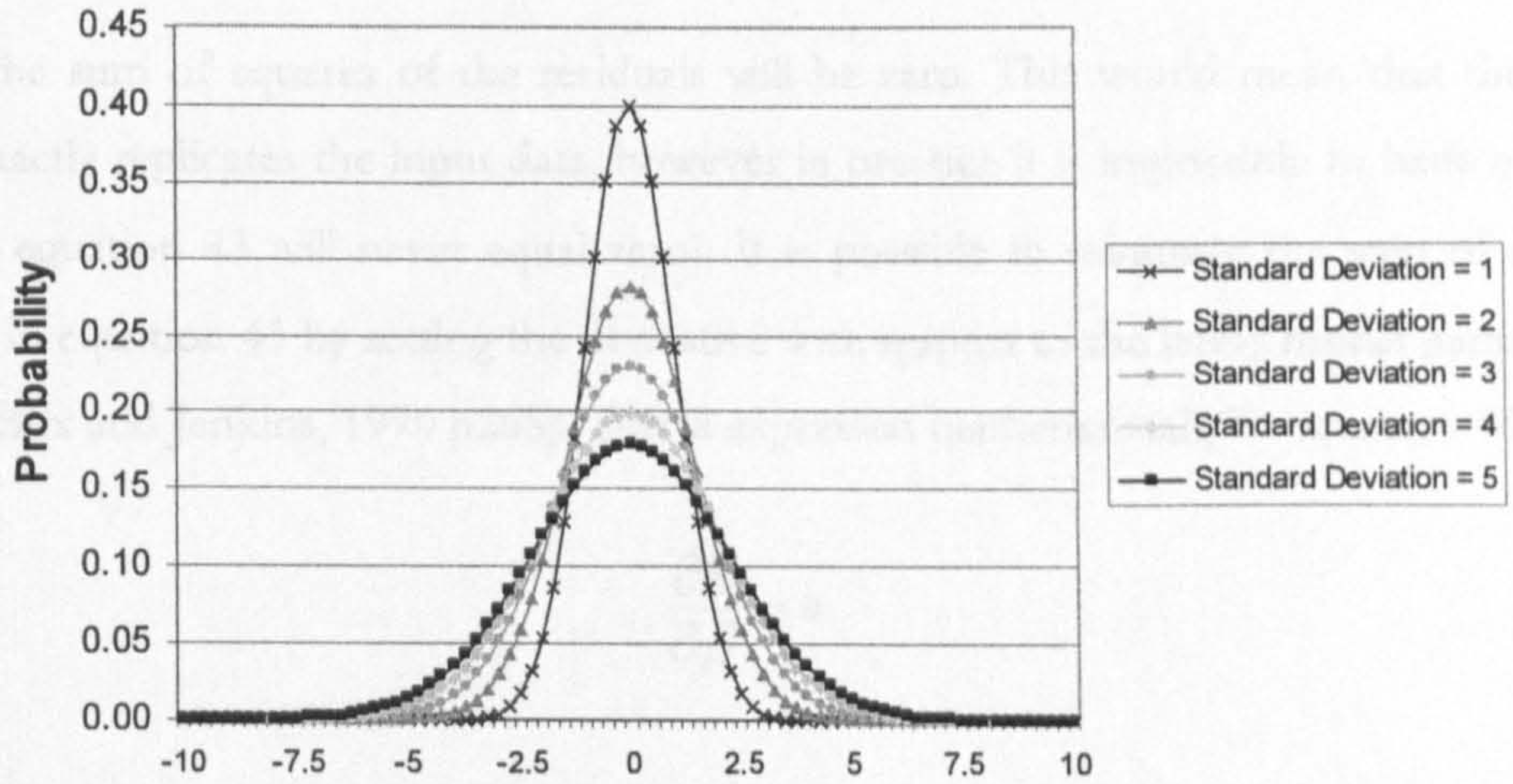

Figure 44: Standard Gaussian Probability Distribution Function

OLS is a method for estimating the parameters of a linear model. The concept of ordinary (or 'linear') least squares is to minimise the difference between the output of a linear model and a set of measured values. In this case, the measured values are the wind speed time series. For the purposes of this thesis, the linear model of interest is the AR(1) model defined in equation defined in equation 40. For simplicity, this can be expressed in more general form in equation 41.

$$y_i = \beta_1 x_{i1} + e_i \tag{41}$$

This can be re-arranged to express the error between the time series value y_i and the linear model $\beta_1 x_{i1}$. This error can be defined as the function 'residuals' r_i (see equation 42). Hence there will be a residual for each time series value.

$$r_i = y_i - \beta_1 x_{i1} = e_i \tag{42}$$

The 'least squares' approach takes the square of each individual residual (i.e. r_i^2). The sum of these squares (S) of the residuals for the whole series can be taken up to the maximum, m. This is displayed in equation 43.

$$S = \sum_{i=1}^{m} r_i^2 \tag{43}$$

Ideally, the sum of squares of the residuals will be zero. This would mean that the linear model exactly replicates the input data, however in practice it is impossible to have no error (i.e. S in equation 43 will never equal zero). It is possible to minimise the sum of squares function in equation 43 by setting the derivative with respect to the linear model parameter β to zero (Box and Jenkins, 1970 p265). This is expressed mathematically in equation 44.

$$\frac{\partial S}{\partial \beta} = 0 \tag{44}$$

By doing this, a value of β_1 is selected which minimises the difference between the measured values and the linear model. For the particular case of the AR(1) model in equation 40, the following parameters are equivalent: $\varnothing_1 = \beta_1$, $z_t = y_i$ and $z_{t-1} = x_{i1}$.

After the AR model coefficient $\varnothing_1$ has been specified, the error is modelled by the noise term a_t (see Figure 44). The variance of the noise term is determined by the residuals themselves. If the residuals show a high amount of scatter around the mean, then the Gaussian distribution will be more spread out (note standard deviation of 5 in Figure 44). If there is less scatter of residuals about the mean, the Gaussian will be less spread out (note standard deviation of 1 in Figure 44). The best way to illustrate these concepts is to apply the methodology to a simple wind speed time series.

4.2.2 Example of Parameter Estimation for Time Series Model

For the single parameter case examined in this thesis, the solution to equation 44 which determines the AR model coefficient $\varnothing_1$ is determined by equation 45, which is re-stated below for convenience (Draper, 1981). The equations for auto-covariance (γ – equation 26) and AR coefficient ($\varnothing$, also called ρ – equation 27) have been presented earlier in the thesis.

$$\phi_1 = \frac{\gamma_1}{\sigma_z^2} = \frac{\frac{1}{N}\sum_{t=1}^{N-1}(z_t - \mu_z)(z_{t-1} - \mu_z)}{\frac{1}{N}\sum_{t=1}^{N}(z_t - \mu_z)^2} \tag{45}$$

t	y_t	$y_t - \bar{y}_t$	y_{t-1}	$y_{t-1} - \bar{y}_{t-1}$	γ_1	σ^2_y
1	9.475	2.155	0.000	0.000	0.000	0.000
2	8.333	1.012	9.475	2.378	2.407	1.025
3	4.805	-2.516	8.333	1.236	-3.110	6.332
4	5.155	-2.166	4.805	-2.293	4.967	4.692
5	6.088	-1.232	5.155	-1.943	2.395	1.519
6	7.415	0.094	6.088	-1.009	-0.095	0.009
7	4.649	-2.672	7.415	0.318	-0.849	7.139
8	7.393	0.072	4.649	-2.449	-0.177	0.005
9	10.564	3.243	7.393	0.296	0.959	10.519
10	9.331	2.010	10.564	3.467	6.968	4.040
Sum	73.210		63.879		13.465	35.281
Average	7.321		7.098		1.496	3.920

Table 27: Sample Wind Speed Model Parameter Estimation

Wind farm SCADA data averaged over 1 day intervals are used as the basis of the wind speed model. To illustrate the concept, Table 27 comprises 10 such consecutive daily values for wind speed taken from wind farm records. $\emptyset_1$ is calculated by taking the average of the γ_1 column (auto-covariance) and dividing by the average of the σ^2_y column (variance). For the data presented in Table 27, the AR (1) parameter $\emptyset_1 = 0.382$.

After the estimate of the AR(1) parameter is made, the variance of the Gaussian noise term can also be estimated. This is achieved by calculating the variance of the sum of the squares of the residuals between the time series data and the model output (Draper, 1981). Table 28 calculates the values of σ^2_{at} as 3.352 and σ_{at} as 1.831 This means that the Gaussian noise term corresponds to a bell curve between standard deviation of 1 and 2 in Figure 44.

t	$y_t - \bar{y}_t$	$\phi_1(y_{t-1} - \bar{y}_{t-1})$	r_i^2
1	0.907497	0.105	0.011003
2	0.471612	-2.988	8.928478
3	-0.87516	-1.291	1.666827
4	-0.74149	-0.491	0.241082
5	-0.38514	0.480	0.230023
6	0.121288	-2.793	7.802105
7	-0.9345	1.007	1.01395
8	0.112886	3.130	9.799144
9	1.323011	0.687	0.471994
Sum			30.16461
σ^2_{at}			3.351623
σ_{at}			1.830744

Table 28: Calculating Variance of Gaussian Noise Term

4.2.3 Simulating Wind Speed Process

Once the AR wind speed model has been classified and the parameters estimated, the model is ready for use in the MCS of wind farm operation. The wind speed can be simulated in a similar manner to the Markov chain: that is by using the concept of the cumulative distribution function, in this case of the Gaussian error term (this is plotted in Figure 45 for the previously calculated standard deviation of 1.830744).

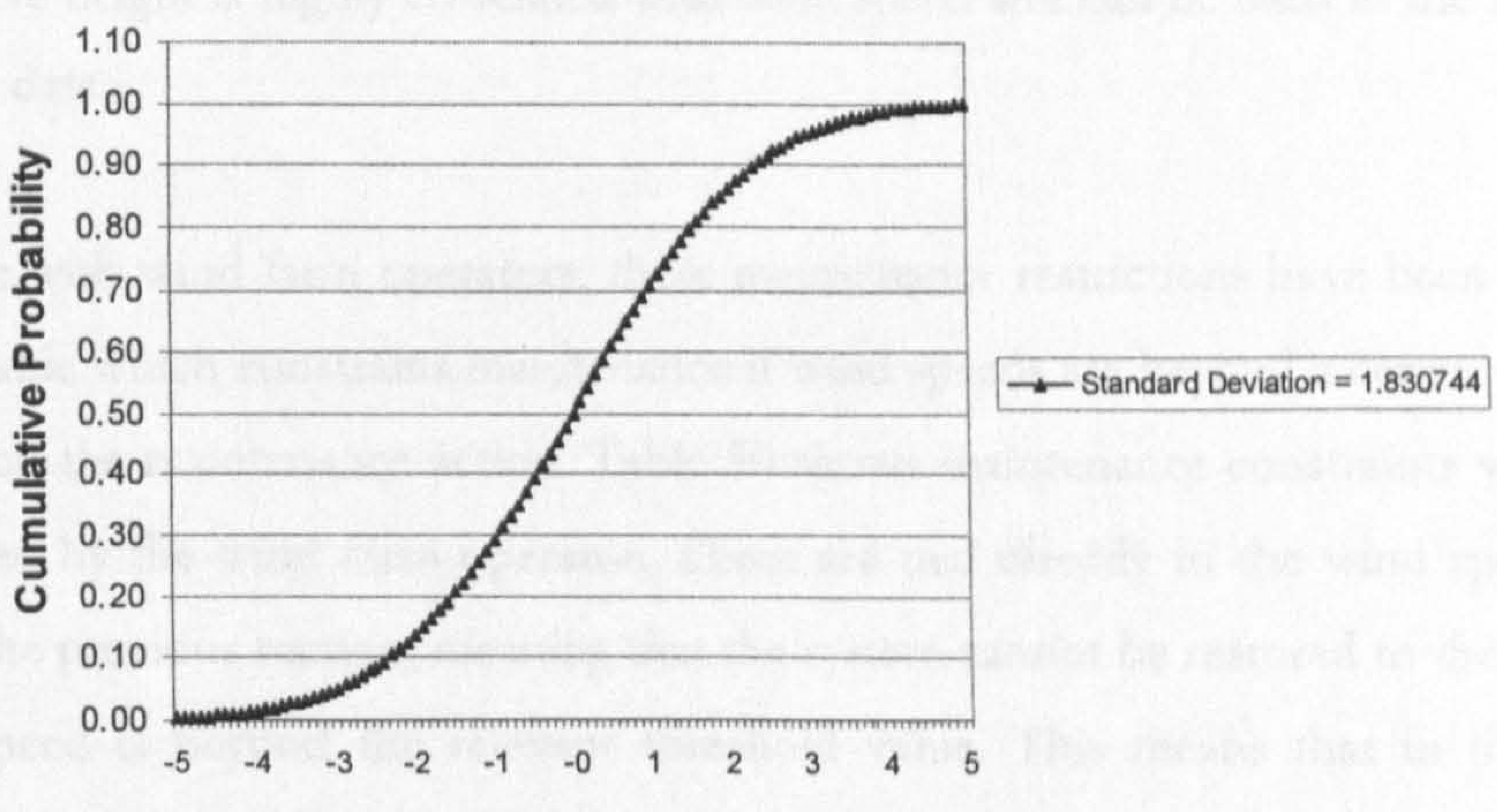

Figure 45: Cumulative Distribution Function for Standard Normal Distribution

Using the model parameters derived in the previous section, a set of wind speeds (z_t) based on the AR(1) model can be simulated using MCS in Table 29. The parameters are expressed in terms of the original autoregressive model in equation 40. Such a small number of samples (10) is not enough to re-create the characteristics of the real wind profile, but demonstrates how the methodology is used to obtain results from data.

PRN	a_t	$z_{t-1}-\mu$	$\phi_1(z_{t-1}-\mu)$	$\phi_1(z_{t-1}-\mu)+\mu$	z_t
0.963408	3.2	2.155	0.82321	8.14421	11.3
0.222233	-1.4	4.023	1.536866	8.857866	7.5
0.315239	-0.9	0.137	0.052283	7.373283	6.5
0.141327	-2.0	-0.848	-0.32383	6.997172	5.0
0.344085	-0.8	-2.324	-0.8877	6.433298	5.6
0.257892	-1.2	-1.688	-0.6447	6.676298	5.5
0.513462	0.0	-1.845	-0.70468	6.616324	6.6
0.139871	-2.0	-0.705	-0.26919	7.051814	5.1
0.130679	-2.1	-2.269	-0.86683	6.454171	4.4
0.170203	-1.8	-2.967	-1.13333	6.187671	4.4

Table 29: Simulated Wind Speed Model

4.2.4 Wind Coupled Maintenance Weather Constraints

Compared to thermal plant, wind farm maintenance is unique in respect of their direct coupling with weather conditions, and in particular, wind speed. The primary reason for this is the use of cranes for heavy lifting of components: however health and safety restrictions are also a major driver. In the offshore case maintenance will also be subject to wave height: however wave height is highly correlated with wind speed and can be used in the absence of wave height data.

Via dialogue with wind farm operators, these maintenance restrictions have been quantified into a rule table which constrains maintenance if wind speeds are beyond a certain threshold, depending on the maintenance action. Table 30 shows maintenance constraints which have been adopted by the wind farm operator. These are tied directly to the wind speed model defined in the previous section, meaning that the system cannot be restored to the up state if the wind speed is beyond the relevant threshold value. This means that in the Markov model, maintenance actions are inhibited in exactly the same way as in real operation.

Wind Speed m/s	Restrictions
>30	No access to site
>20	No climbing turbines
>18	No opening roof doors fully
>15	No working on roof of nacelle
>12	No going into hub
>10	No lifting roof of nacelle
>7	No blade removal
>5	No climbing MET masts

Table 30: Wind Speed Maintenance Constraints

The wind speed model and wind-coupled maintenance constraints have been demonstrated in this section. The final and highest-level element of the model architecture in Figure 6 is the asset management policy model. It has been mentioned previously that TBM and CBM are the two main competing methods of applying maintenance to wind turbines. The next sections explicitly define how TBM and CBM are modelled.

4.3 Defining a Maintenance Model

Maintenance models have been discussed in section 3.4 for generic cases. As mentioned previously, the crux of maintenance modelling is how to characterise the physical effects of maintenance. The economic impacts can be quantified more easily as they can be readily measured in the form of annual maintenance expenditure or costs associated with individual repairs, equipment hire and labour.

A substantial body of research exists on the subject of maintenance modelling and technical impact of maintenance. Much of it is in the domain of operational research (OR), which has its origins in military applications. An early example of OR in the field of maintenance modelling can be found in McCall (1965). The author presents a review of maintenance models from the early history of O&M modelling. However, at this point in the chronology of maintenance modelling, all reviewed models were simple two-state systems (i.e. functional or non-functional). Therefore by definition the repair model must restore the system to 'as good as new' in this case, thus only replacements rather than repairs are modelled. More recently, Cho and Parlar (1991) reviewed literature on maintenance models focusing on multi-unit models. Most of the reviewed studies were concerned with optimisation of spare part stocks and buffers. Nearly all the maintenance models assumed component replacement after failure, rather than repair. Restoration of the system to 'as good as new' state was universally assumed as the technical impact of maintenance, in a similar vein to this thesis.

Several methods have been developed in the OR domain to account for imperfect maintenance. Phann and Wang (1996) present a summary of imperfect maintenance models, which do not always assume 'as good as new' repairs. The most basic of these, called the p, q rule (also called the Brown-Proschan model), simply models a probability of the maintenance having no effect (q) and the remaining probability is 'as good as new' repair p, where q=1-p. The authors go to explain more complex models such as p, q with time dependence: q(t)=1-p(t). Other models mentioned by the authors are based on cumulative damage models using many states, where the level of recovery after maintenance is dependent on various functions.

These latter models mentioned by Phann and Wang (1996) are a much more in-depth representation than required for the models in this thesis and therefore have little relevance to this discussion. The p, q rule has been considered for inclusion in this thesis but is not implemented due to a lack of suitable data on the effects of maintenance, especially in the wind energy domain.

Imperfect maintenance models are also adopted in the recent papers of Barata et al. (2002) and Marseguerra et al. (2002) which have been discussed in chapter 3. It is again noted that the detailed multi-state model of deterioration and repair in these papers is not conducive to parameter estimation and is thus impractical when an implementation is desired, as in this thesis. Borgonovo et al. (2000) employ the Brown-Proschan model for imperfect maintenance mentioned earlier, which represents a good compromise between more realistic modelling of maintenance effects and simple parameter estimation of p and q (see earlier explanation). It was decided that not enough accessible data currently exists in the wind farm domain to properly implement this model: therefore it has not been considered in this thesis. Similarly, the imperfect maintenance models proposed by Endrenyi and Anders (2006) are a good compromise between model detail and practicality, being quite similar to the Brown-Proschan model of imperfect maintenance. For the same reasons (lack of data) this imperfect maintenance model is not adopted in this thesis.

Returning to the theme of modelling of perfect maintenance actions, recently published papers still often use the assumption of restoring the system to the 'as good as new' condition. Studies by Schneeweiss (1995), Badia et al. (2002), Bris et al. (2003), Cui and Xie (2005), Duarte et al. (2006), Zio et al. (2006) and Zio and Podofillini (2007) all conform to the assumption of 'as good as new' repair. This may be due to a lack of data (as in this thesis), the need to keep the model simple in order to solve it more easily, a lack of faith in the validity of more complex models of maintenance, or simply that the effects of maintenance are not at the heart of the study. In this thesis, the pragmatic view is taken that since wind turbine maintenance data are scarce, complex maintenance models cannot be properly implemented. The 'as good as new' maintenance model, although simplistic, represents an adequate assumption which will be adopted for the rest of the thesis.

Having established the underlying technical assumptions in the maintenance model, the next section expands the explanation of the maintenance models for TBM and CBM applied specifically to the system defined in Figure 33, using case studies to help visualise the mechanics of the maintenance models.

4.3.1 Application of Time Based Maintenance

The TBM model is implemented to emulate the situation at currently operational wind farms. This means that the frequency of TBM actions is once every 6 months for onshore wind farms and once every 12 months offshore. The equipment is restored to the fully up state (i.e. s_1) following the maintenance actions ('good as new' condition). Costs are incurred according to the component-specific repairs which need to be conducted.

As an example, consider s_1 from the system constructed in Figure 33. A case study of the TBM process is illustrated in Figure 46. Assume the system deteriorates to s_4 ('current system state' on left hand side Figure 46) over the course of a 6 month maintenance interval (182 days). This means that the gearbox (C1) and generator (C2) will need repair actions to restore them to the fully up state s_1. Assuming a 2MW WT, taking component costs from Table 21 and setting α = 0.1, this means that the incurred component repair costs total £15,000 (see calculation in Figure 46). Additional costs C_{LAB} and R_{LOST} are also incurred and deducted from the WT revenue stream, R.

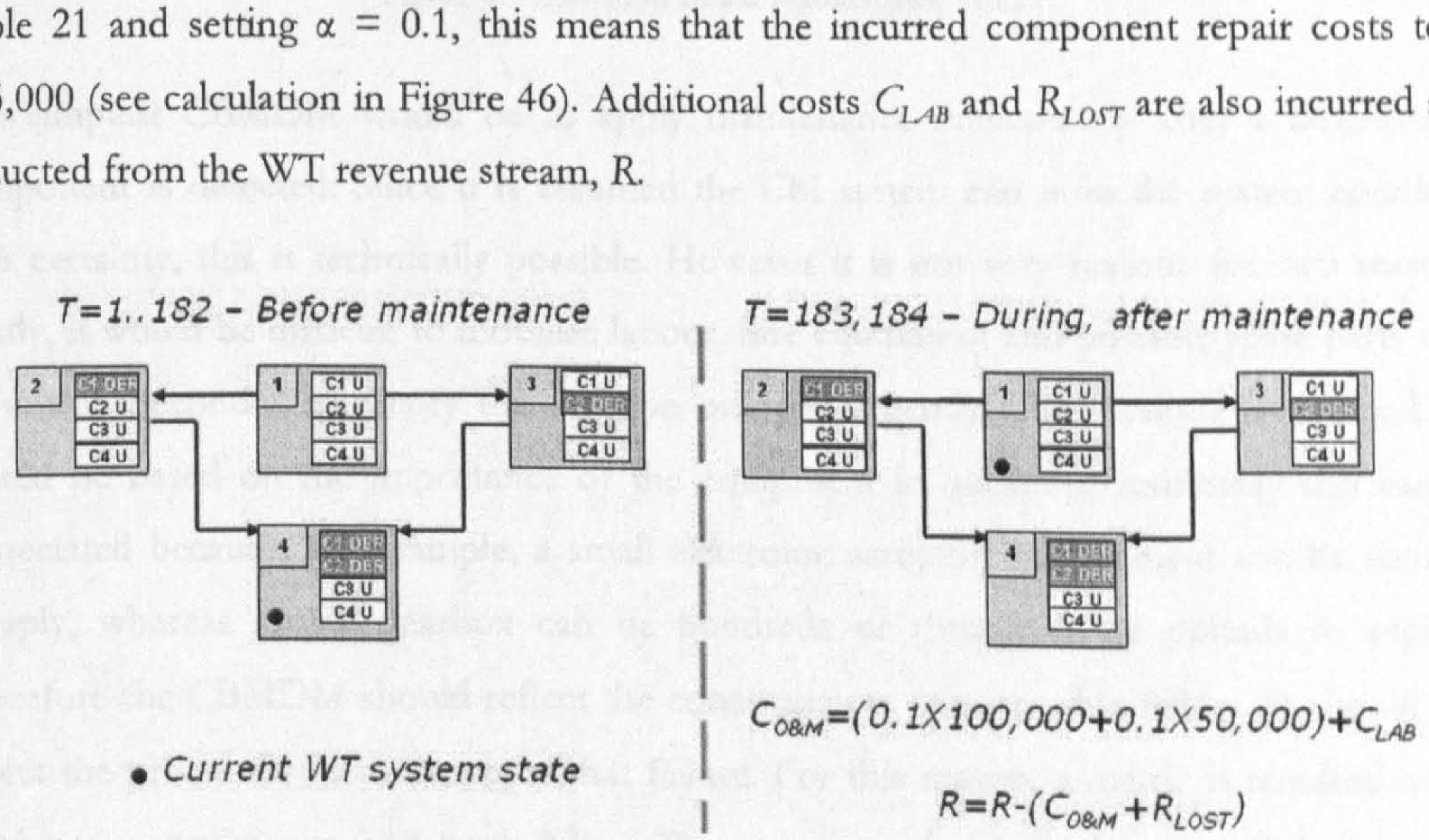

Figure 46: Time Based Maintenance for Wind Turbine Markov Model

4.3.2 Application of Condition Based Maintenance

The concept of risk and its use as a metric to couple condition and maintenance actions was discussed in section 3.4.4. The actual mechanism of this coupling is visualised in Figure 47. The CM system monitors the state of the WT components and the information is fed into a 'condition-based maintenance decision model' (CBMDM). Figure 47 shows that the maintenance decisions will be based on the output of the CBMDM rather than carried out on a fixed frequency basis, as with TBM. This difference in maintenance paradigm is central to this thesis as the main purpose of this research is to establish the techno-economic benefits of adopting CBM.

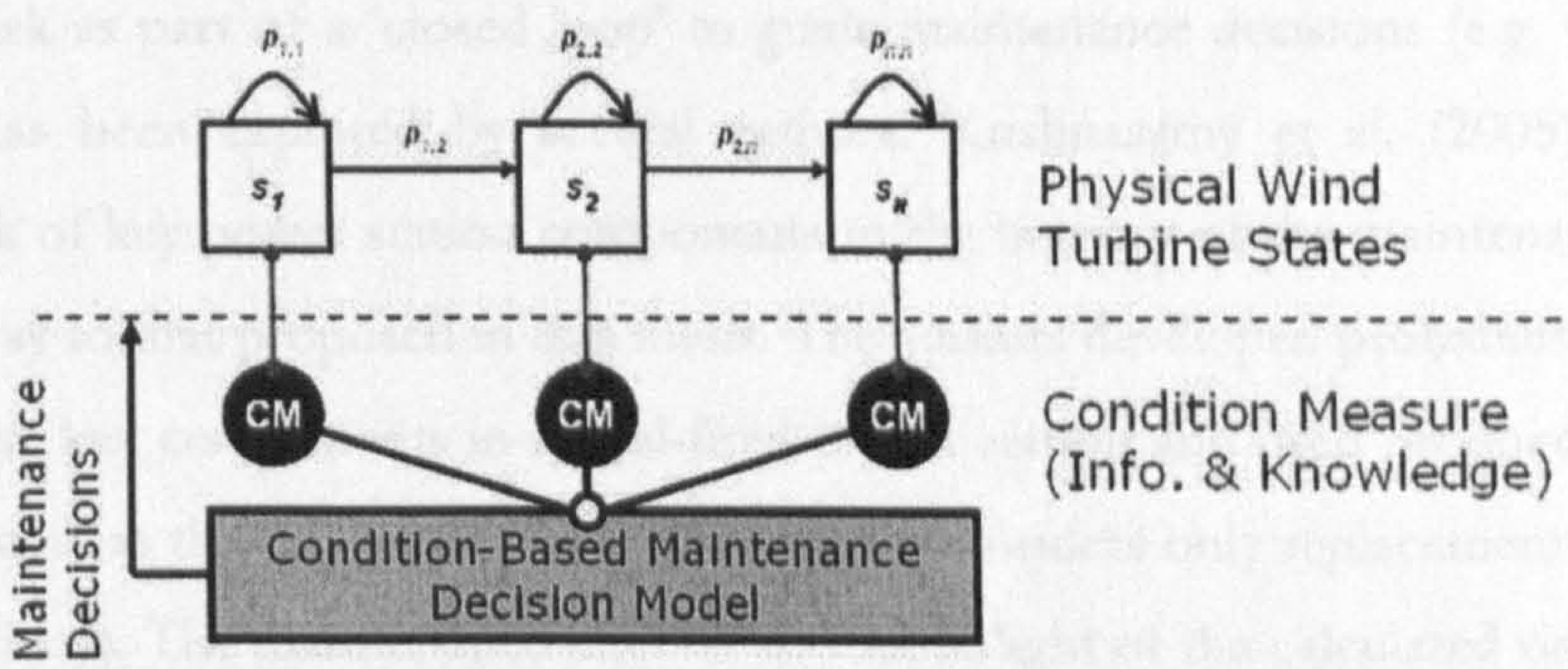

Figure 47: Condition Based Maintenance Model

The simplest CBMDM would be to apply maintenance immediately after a deteriorated component is detected. Since it is assumed the CM system can infer the system condition with certainty, this is technically possible. However it is not very realistic for two reasons. Firstly, it would be difficult to mobilise labour, hire equipment and possibly spare parts with no notice. Secondly, in theory the decision on how urgently CBM actions are carried out should be based on the importance of the equipment in question. Intuitively this can be appreciated because, for example, a small electronic assembly replacement can be sourced cheaply, whereas a WT gearbox can be hundreds of thousands of pounds to replace. Therefore the CBMDM should reflect the consequences of a possible failure. It should also reflect the probability of occurrence that failure. For this reason, a metric is required which combines consequence and probability. The concept of risk is the most suited to this purpose.

A very comprehensive review of risk analysis procedures was produced by Backlund and Hannu (2002). The authors focused on the practical issues associated with implementation of maintenance policies informed by risk analysis. In particular they were interested in how the probability and consequence (impact) of failures could be quantified, an issue often ignored in the more theoretical literature. The pragmatic view of the authors highlighted the need for data to estimate the parameters, but allowed for the use of expert judgement, especially to calculate the frequency (probability) of failure events. This mirrors the approach adopted in this thesis, whereby the failure probabilities have been estimated by domain experts due to a lack of data (see Table 24 earlier in this chapter). Schwan et al. (2006) use risk to analyse overall supply reliability in distribution networks. The supply interruption risk from different maintenance scenarios is used to inform maintenance policy decisions.

The use of risk as part of a 'closed loop' to guide maintenance decisions (e.g. CBMDM in Figure 47) has been explored by several authors. Krishnasamy et al. (2005) linked the calculated risk of key power station components to the urgency of the maintenance interval, in a similar way to that proposed in this thesis. The authors developed probabilistic reliability models for the key components in a coal-fired power station and used production loss and replacement cost as the impact of failure (this thesis considers only replacement cost for the sake of simplicity). The maintenance interval was set in light of the calculated risk. The same authors in a more recent publication (Khan et al, 2008) focus on availability of oil-fired generating units, with the risk model specifying when maintenance actions should be carried out.

For the models in this thesis, the risk associated with each state ($s_1, \ldots s_n$) in the WT Markov model can be calculated by quantifying the probability of failure events (pr_e), impact of those events (im_e) and applying equation 46 for each state.

$$\begin{bmatrix} Risk_{s_1} \\ \cdot \\ \cdot \\ Risk_{s_n} \end{bmatrix} = \begin{bmatrix} \sum_e s_1 pr_e \times s_1 im_e \\ \cdot \\ \cdot \\ \sum_e s_n pr_e \times s_n im_e \end{bmatrix} \tag{46}$$

The probability of failure events can be calculated from the Markov chain transition probabilities, and have been estimated previously in the parameter estimation section 4.1.7. Table 24 earlier in this chapter had derived these probabilities for the gearbox, generator and rotor blade. For the purposes of the CBMDM, the impact, im_e of the individual failure events, e, is considered to consist only of component replacement cost. This is a simplification, as equipment hire costs and production loss are two other impacts which will make the overall impact greater. However this assumption is held for the rest of the thesis.

Table 21 presented component replacement costs using proportions of the WT capital cost as derived in McMillan and Ault (2008). Equation 46 is applied for these values of probability of failure events (pr_e) and impact of those events (im_e) and the resulting risk levels displayed in Figure 48. These states can be classified according to their risk: low risk (risk<500), medium risk (500<risk<1500) and high risk (risk>1500).

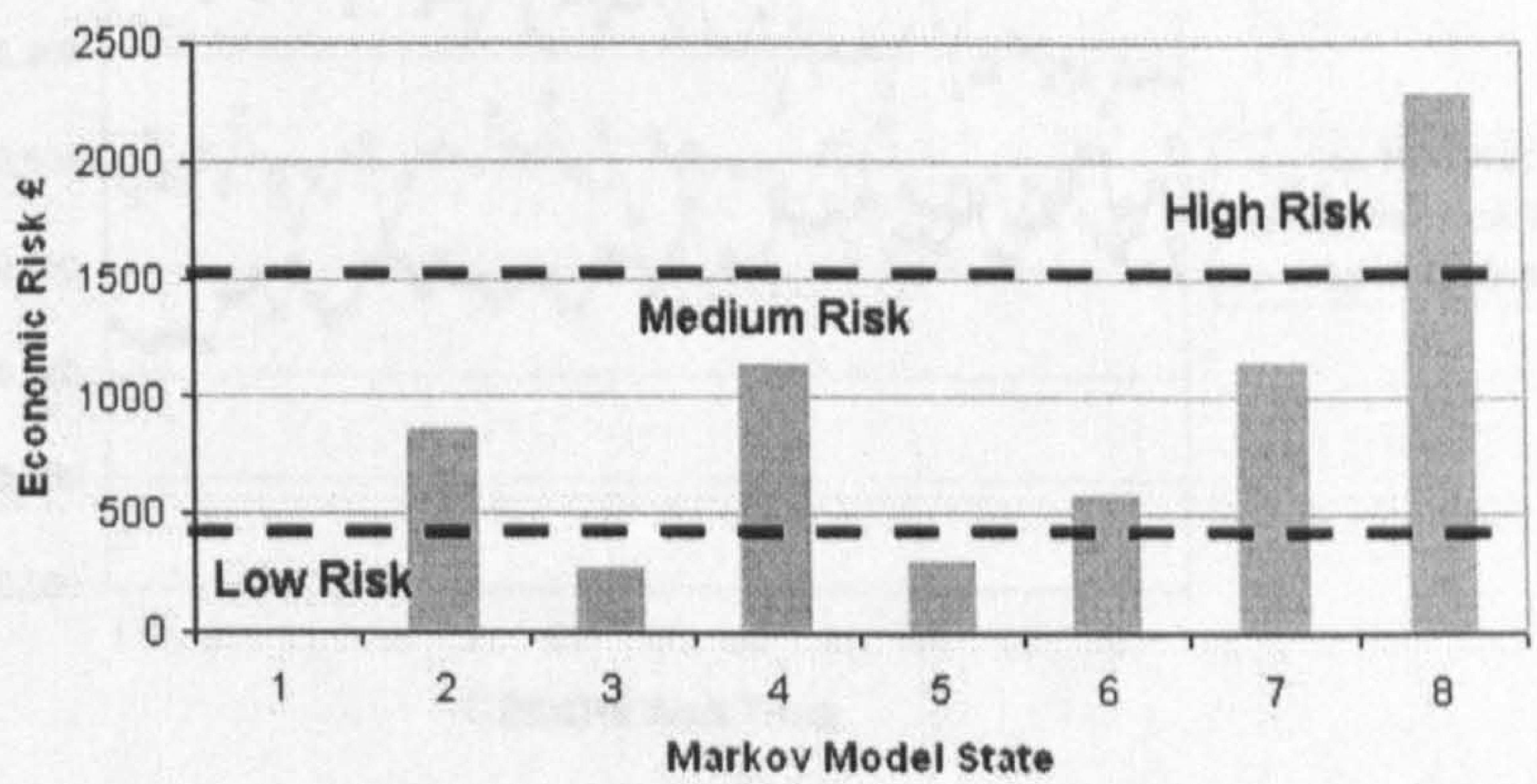

Figure 48: Risk for Each WT Markov Model State

These three risk levels can be utilised to model CBM, since they are a function of the system condition and also reflect the importance of the components. Therefore, instead of a fixed-period maintenance policy (TBM), the risk levels defined in Figure 48 can be used to determine how urgently maintenance should be carried out (i.e. influencing the maintenance schedule). How exactly the risk corresponds to the magnitude of the maintenance interval depends on the characteristics of the system. It is possible to derive values for each maintenance interval, which balance economic and technical impacts of maintenance, by running sensitivity analyses on the system. This procedure is outlined in the next section.

4.3.3 Derivation of Risk-Based CBM Maintenance Interval

The impact of the risk-based CBM interval (CBMDM wait time) is observed by changing the maintenance interval for one of the three risk levels while holding the other two maintenance intervals constant at 728 days (2 years). This large value was chosen to eliminate any dependence on the other maintenance intervals. Figure 49 shows the WT revenue stream as a function of CBMDM wait time, which is varied from 1 to 60 days. It can be seen that over this span of maintenance interval time (60 days, ~2 months), the impact of increasing the maintenance interval is different depending on the risk level. The uneven nature of the plots illustrates the significant uncertainty in the simulation results, however despite this, two clear trends can be observed in Figure 49.

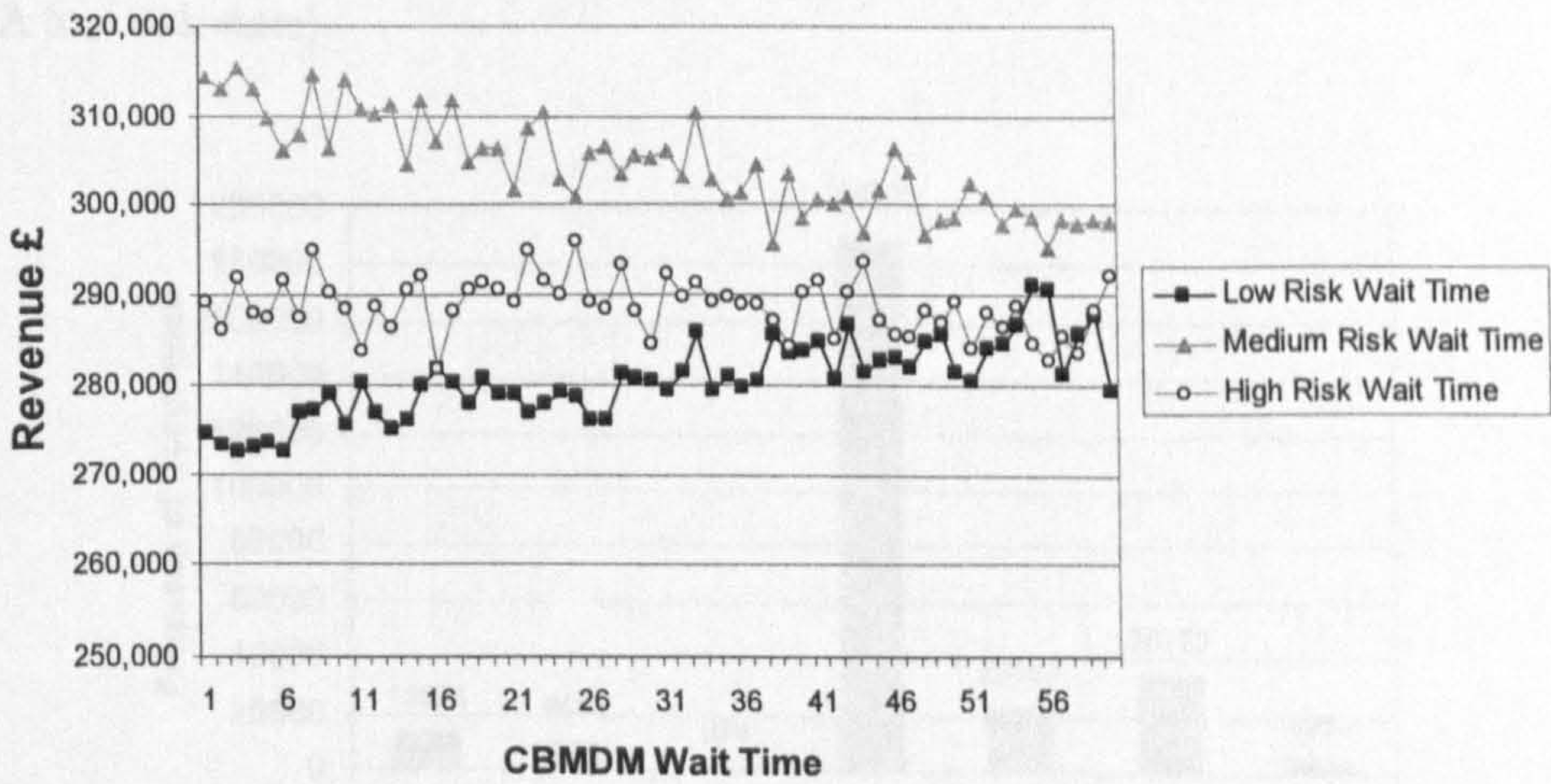

Figure 49: Revenue Impact of Risk-Based CBM Intervals for All Risk Levels

The first is that the WT revenue increases as the low risk wait time is increased from 1 to 60. This means that it is more cost-effective to delay a low-risk CBM action than to carry it out quickly.

The second clear trend from Figure 49 is that the WT revenue decreases as the medium risk wait time is increased (i.e. the opposite effect than for the low risk state). This implies that medium risk states should be repaired relatively urgently. This is because the longer the medium risk CBMDM time interval becomes, the less WT revenue is gained, as shown in Figure 49. This is clearly a negative outcome for the wind farm operator.

Perhaps the most surprising plot in Figure 49 is that for the high risk state. The WT revenue does not appear to be very well coupled with the CBMDM wait time. The WT revenue remains at a stable level throughout the CBMDM wait time range of 1 to 60 days. Since the high risk state represents the case of high product of probability and impact, Figure 49 is counter-intuitive. It would be expected that the high risk state be the most clearly coupled with CBMDM wait time.

The reason for the surprising result in Figure 49 can be explained by examining the relative frequency of occurrence of the 7 states subject to the CBMDM (states 2-8). This is displayed in Figure 50 for a total of 436,800 MCS trials. It is observed that the distribution between the states is uneven, with the system spending a high proportion of the simulation period in state 5 (A low risk state).

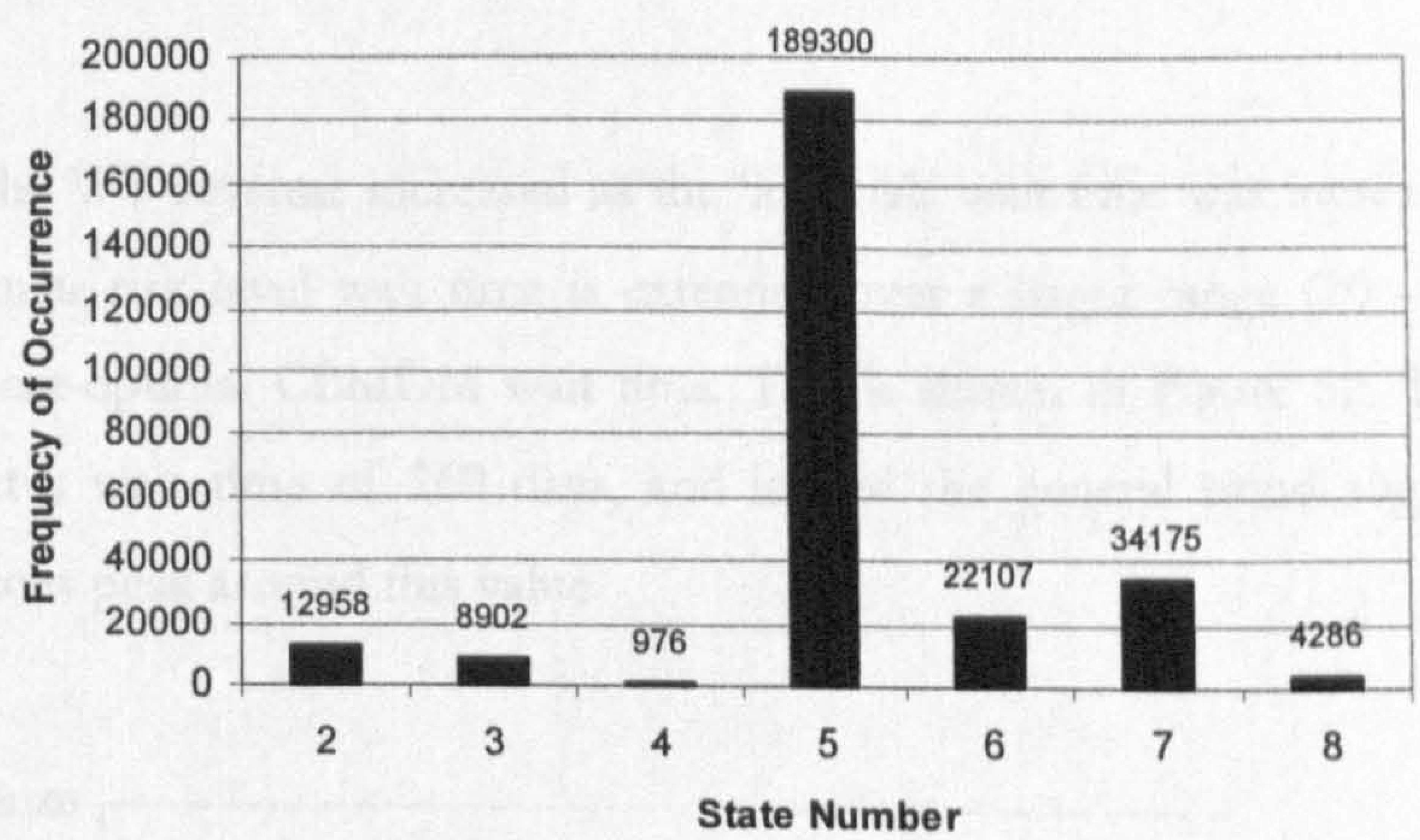

Figure 50: Frequency of Occurrence of States 2-8 during MCS

These states (2-8) can be grouped according to their level of risk (see Figure 48). The probability of each of the three risk levels (low, medium and high) can be calculated by summing the 'frequency of occurrence' of each risk level and then dividing by the total number of MCS trials (436,800). For example, the probability of being in a low risk state can be calculated by summing the state frequency for states 3 and 5 (8902+189,300=198,202) and dividing by 436,800 to get a probability of 0.454. The resulting probabilities for all risk levels are shown in Figure 51.

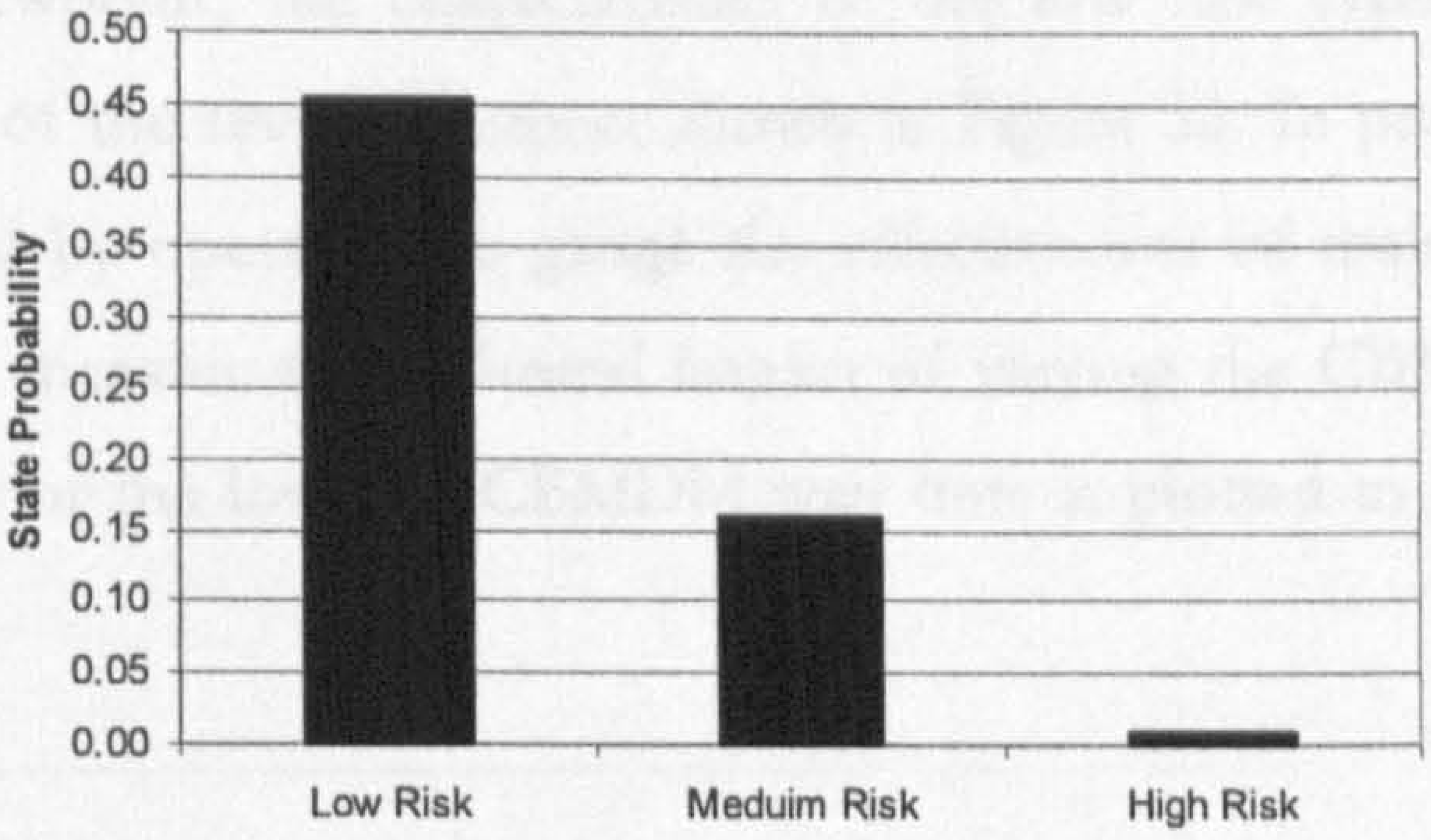

Figure 51: Probability of Risk Level Occurrence during MCS

Figure 51 explains the relative lack of coupling between the maintenance interval associated with high risk level in Figure 49 and the WT revenue. There is little effect because high risk states are encountered so infrequently, as shown in Figure 51. The other two risk levels have a more dominant effect on WT revenue because the associated Markov states occur much more frequently.

In Figure 49, the WT revenue increased as the 'low risk' wait time was increased from 1 to 60. This particular risk level wait time is extended over a larger range (10 – 600 days) to establish the near-optimal CBMDM wait time. This is shown in Figure 52. The maximum value occurs at a wait time of 260 days, and indeed the general trend suggests that the characteristic does peak around this value.

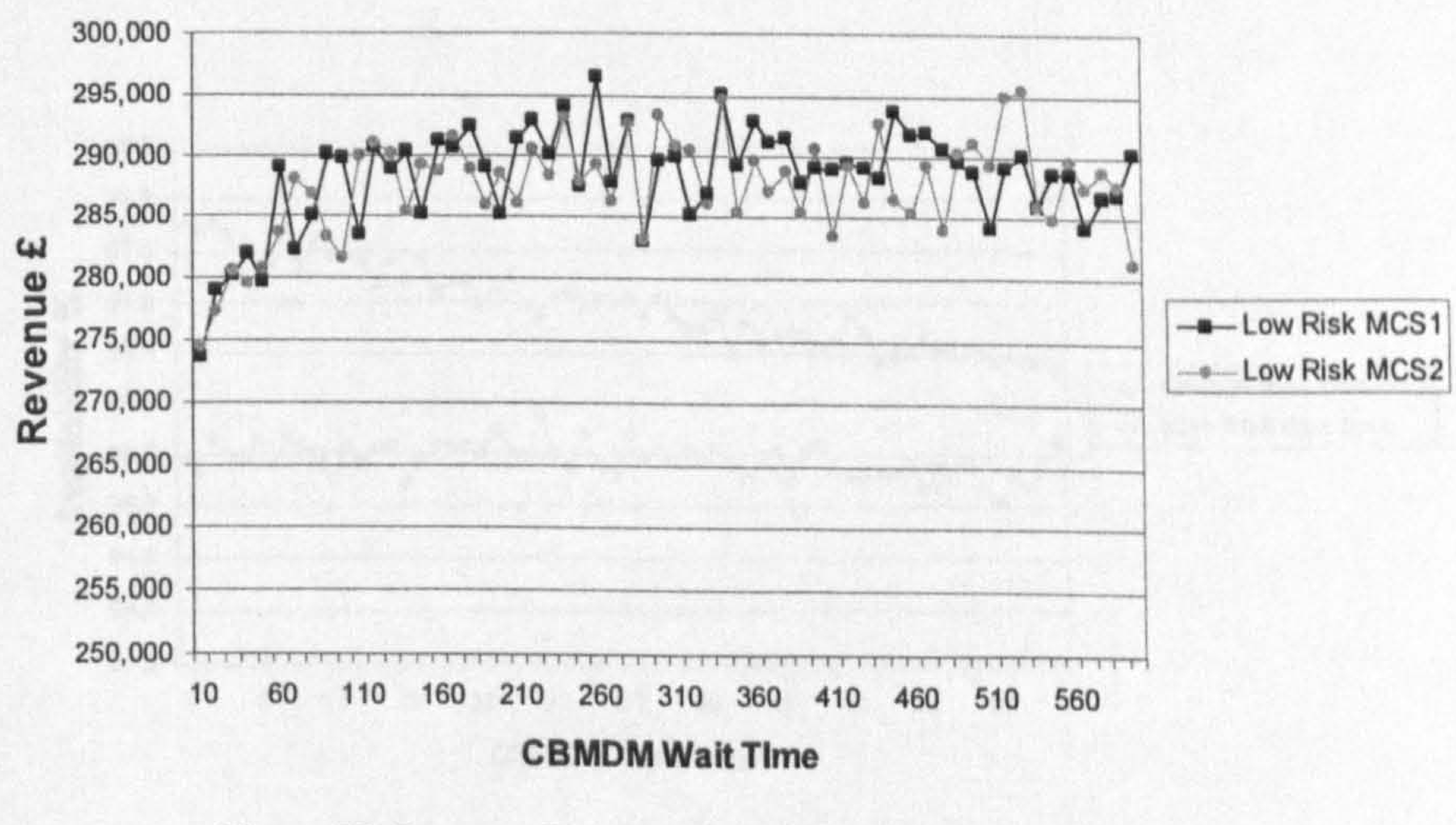

Figure 52: Revenue Impact of Low Risk Maintenance Interval

From a technical viewpoint, the characteristics of the low risk maintenance interval are different from those of the revenue impact shown in Figure 52. In particular, availability is the metric often used by operators to gauge the effectiveness of maintenance policy. The availability is used to measure the technical impact of varying the CBMDM wait time. The impact on availability of the low risk CBMDM wait time is plotted in Figure 53 is used for this purpose.

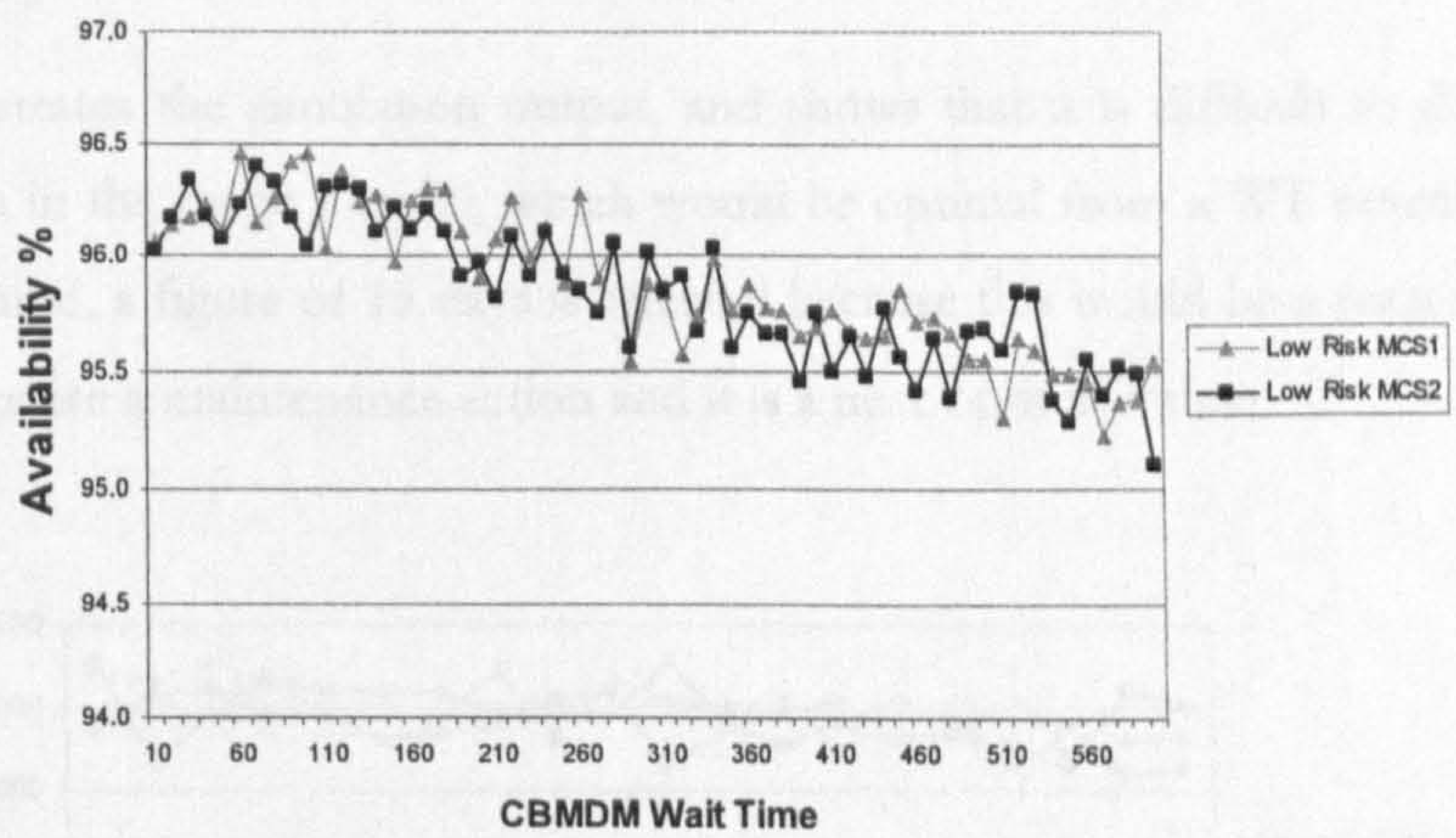

Figure 53: Availability Impact of Low Risk Maintenance Interval

Although Figure 52 suggested a revenue-optimal wait time of around 260 days, Figure 53 clearly shows that this maintenance wait time would not maximise WT availability. Therefore, a compromise value of 100 days is adopted in this thesis, which keeps both availability and revenue at a relatively high level. In terms of the other two risk levels (medium, high), the technical and economic impacts are in closer agreement.

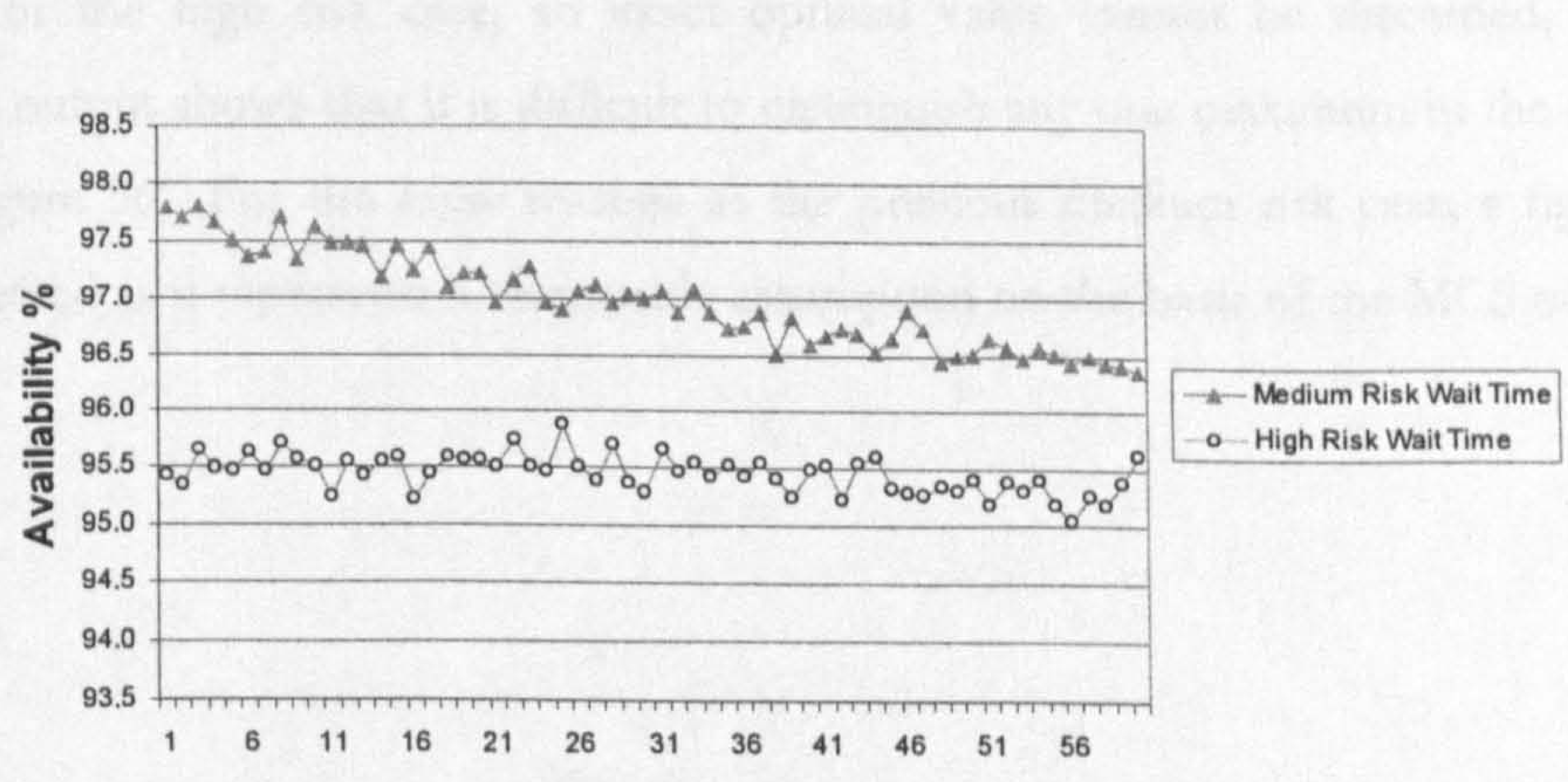

Figure 54: Availability Impact of Medium and High Risk Maintenance Interval

Figure 54 shows that the general trends for availability are the same as the revenue trends in Figure 49, and therefore only revenue impact is discussed. Inspection of Figure 49 suggests a value of less than 20 for the medium risk CBMDM wait time. Three Monte Carlo simulations for the range 1 to 20 were run in order to estimate a near optimal value for the medium risk maintenance interval.

Figure 55 illustrates the simulation output, and shows that it is difficult to distinguish any one maximum in the range 1 to 20, which would be optimal from a WT revenue viewpoint. With this in mind, a figure of 15 days is selected because this would be a reasonable amount of time to organise a maintenance action and it is a near-optimal value.

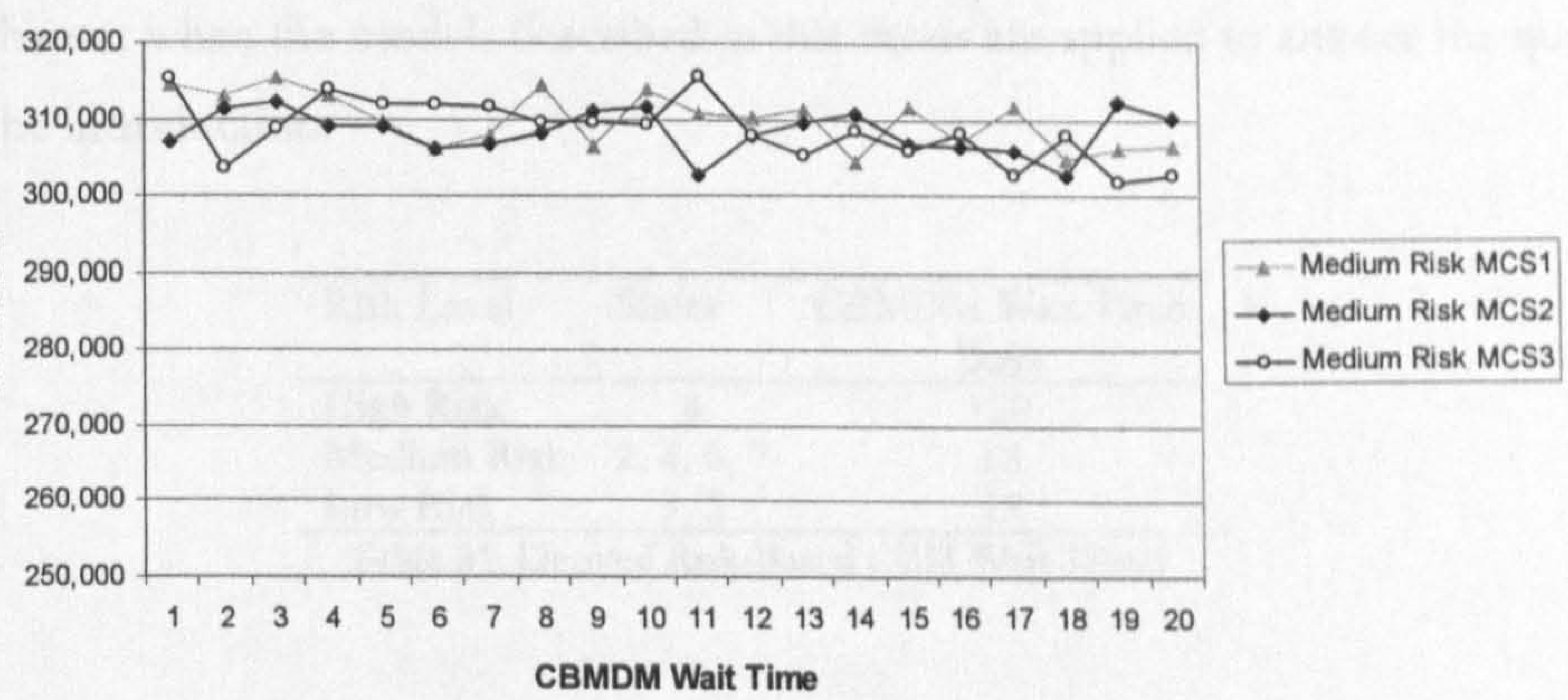

Figure 55: Revenue Impact of Medium Risk Maintenance Interval

Similarly for the high risk case, an exact optimal value cannot be discerned, since the simulation output shows that it is difficult to distinguish any one maximum in the range 1 to 20 (see Figure 56). For the same reasons as the previous medium risk case, a figure of 15 days is selected as it represents a reasonable assumption on the basis of the MCS output.

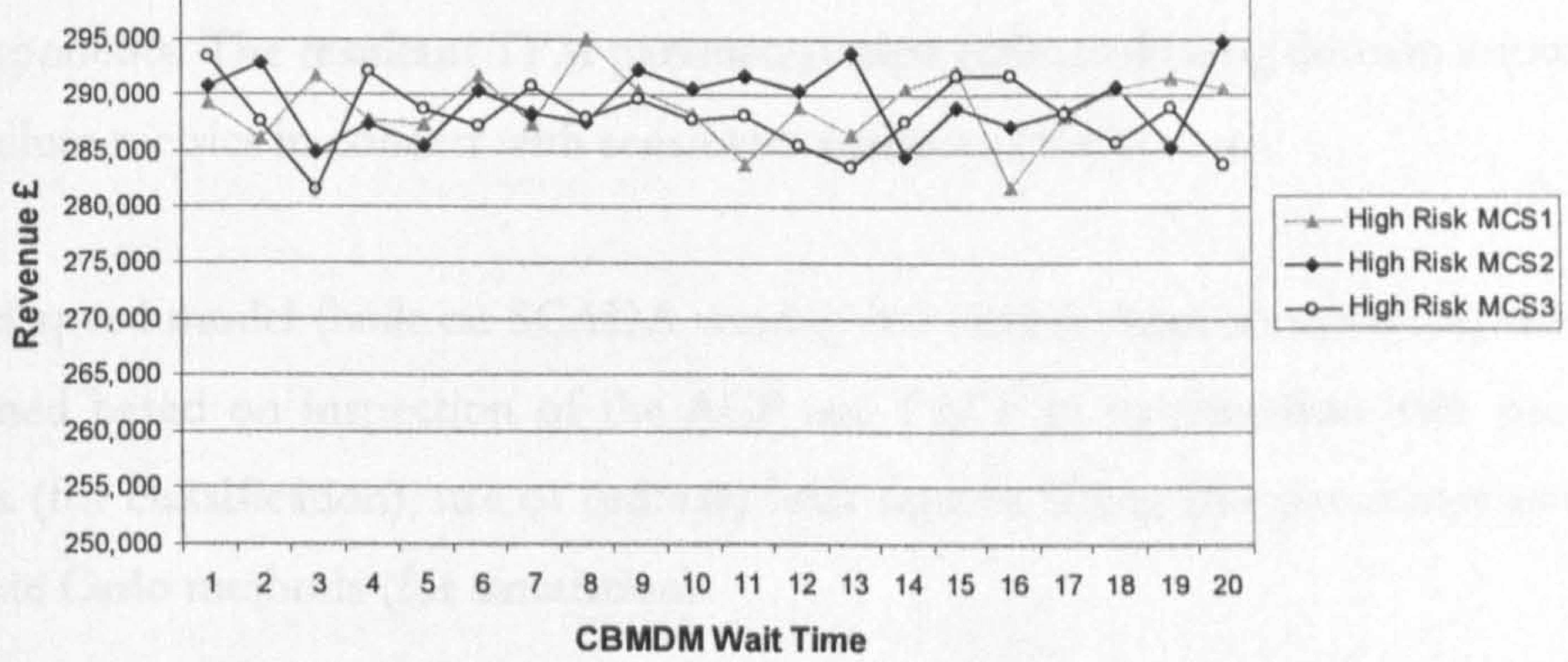

Figure 56: Revenue Impact of High Risk Maintenance Interval

The CBMDM wait times have been established based on the sensitivity analyses in this chapter. The values are summarised in Table 31. These will be used as model parameters in the next chapter when the models described in this thesis are applied to answer the questions posed in the introduction.

Risk Level	States	CBMDM Wait Time Days
High Risk	8	100
Medium Risk	2, 4, 6, 7	15
Low Risk	3, 5	15

Table 31: Derived Risk-Based CBM Wait Times

4.4 Chapter 4 Summary

This chapter has shown the methodology which has been developed to quantify the technical and economic aspects of wind farm maintenance policy, with particular focus on CBM. The three elements of modelling, which were first illustrated in Figure 6 (WT component deterioration and failure, wind speed and energy yield, and asset management policies), were each summarised in this chapter.

The physical WT deterioration and failure model, based on a Markov chain, comprised four key WT components (gearbox, generator, rotor blade and E&E). These were selected for inclusion in the model based on their annual failure rate contribution, downtime duration on failure and expert opinion of a wind farm operator. CM can be applied to three out of the four components. The resultant TPM parameters were estimated using domain knowledge & annual failure metrics in concert with sensitivity analysis of the system.

The wind speed model (built on SCADA wind speed records from an operating wind farm) was defined based on inspection of the ACF and PACF in combination with pre-defined heuristics (for classification), use of ordinary least squares fitting (for parameter estimation) and Monte Carlo methods (for simulation).

Finally, the representation of TBM and CBM was explained. In the case of TBM this was achieved through use of a deterministic maintenance interval which depends on accessibility to the wind farm and is derived from industrial domain knowledge. CBM is modelled through direct knowledge of the Markov state in the decision-process which informs how urgently maintenance should be performed based on the perceived risk of the current system state. The risk classifications are system-specific and the near-optimal magnitude of the CBM interval is determined via simple sensitivity analyses of the system. This classification took the balance between both economic and technical impacts into account.

All maintenance actions are the subject of weather constraints which hamper repair efforts as in real-life wind farm operation. These are simply added as constraints to the Markov model.

Chapters 3 and 4 have explained the rationale of the methodology proposed in this thesis, and have also explained all modelling aspects through use of simple examples. With this groundwork in place, the next chapter contains applications of these techniques. Since the key aspects of wind farm operation and wind turbine characteristics have been captured, it should be possible to answer the key research questions posed at the beginning of this thesis.

4.5 Chapter 4 References

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Author Discussions

Yusuf Patel, (2005) – Author discussions. Wind Farm operator.

Matt Smith, (2006) – Author discussions. Wind Turbine Condition Monitoring System Manufacturer

5 Application of Methodology and Models – Onshore Wind Turbine Model

The methodology which has been developed throughout the duration of this research has been outlined. In this chapter the methodology is applied to answer the research questions posed in the introduction of the thesis. These research questions are re-stated below.

- Is condition-based maintenance for wind turbines cost-effective?
- What is the economic value of CBM for WT units relative to other maintenance?
- What is the technical benefit of CBM for WT units relative to other maintenance?
- What are the necessary conditions for cost-effective WT CM systems?
- Do offshore conditions enable economic viability of wind turbine CM systems?

5.1 Onshore Wind Turbine Model

The procedure adopted for answering these questions is to conduct case studies which explore the issues of interest. These case studies range from validation of the models themselves, to establishing base case results, to observing the effect of adjusting key parameters in the models. A summary description of the case studies conducted in this chapter is provided in Table 32.

Name of Case Study	Thesis Section Number
Model Validation Procedure	5.1.1
Onshore Base Case Evaluation of CM Benefit	5.1.2
Increased Component Costs	5.1.3
Onshore Wind Turbine Base Case Sensitivity to Component Reliability Levels	5.1.4
Reparability of Components	5.1.5
Effect of Maintenance Action Costs	5.1.6
Effect of Downtime Variation	5.1.7
Impact of Wind Regime	5.1.8
Impact of Imperfect CM Diagnosis	5.1.9
Comparison of Results with Existing Research	5.1.10

Table 32: Summary of Case Studies

The model assumptions are those adopted in section 4.1.9. In terms of the O&M cost expression (equation 38), the following parameters are defined: α=0.1 (estimated) and β=0.6 (derived from gearbox data in Ribrant & Bertling, 2007). This means that a component repair incurs 10% of the full replacement cost, and that after a failure, a replacement is necessary in 60% of cases. Capital costs, downtime and other model parameters are summarised in Table 33: all of these parameters have been discussed previously. The wind speed model was derived from 1 year of SCADA data averaged over 1 day time periods. The mean wind speed over 364 daily samples is 6.95m/s. The model was identified as AR(1) using the techniques in section 3.3.1. OLS fitting (see 4.2.1) was used to estimate the parameters (θ_1= 0.5077, variance of a_t = 5.706) which were then used in the MCS.

Metric	Gearbox	Generator	Rotor Blade (1)	E&E	ROCs per MWh
Replace Cost	£100,000	£50,000	£90,000	£5,000	# / £
Downtime	30 Days	21 Days	30 Days	1 Days	1.0/ 40
WT Rating	C_{LAB}	C_{EO}	Maintenance Freq.	Base Case Failure Rates	
2MW	£1,200	£1,500	6 months	Tavner et al. 2007	

Table 33: Onshore Model Parameter Study

The wind turbine used for the model validation study and subsequent onshore analysis is a 2MW machine (Vestas, 2008) and has the power curve displayed in Figure 57, which was sampled and fitted to the theoretical energy yield expression (equation 33). Other technical aspects of the power curve are summarised in Table 34, showing that this combination of WT and wind profile results in a capacity factor of 29.7%.

WT Rating	Rotor Radius	Cut in, Rated, Cut out Wind Speed	Capacity Factor
MW	M	m/s	% @ mean wind speed 6.95m/s
2	40	4, 14, 25	29.7

Table 34: 2MW Onshore Wind Turbine Characteristics

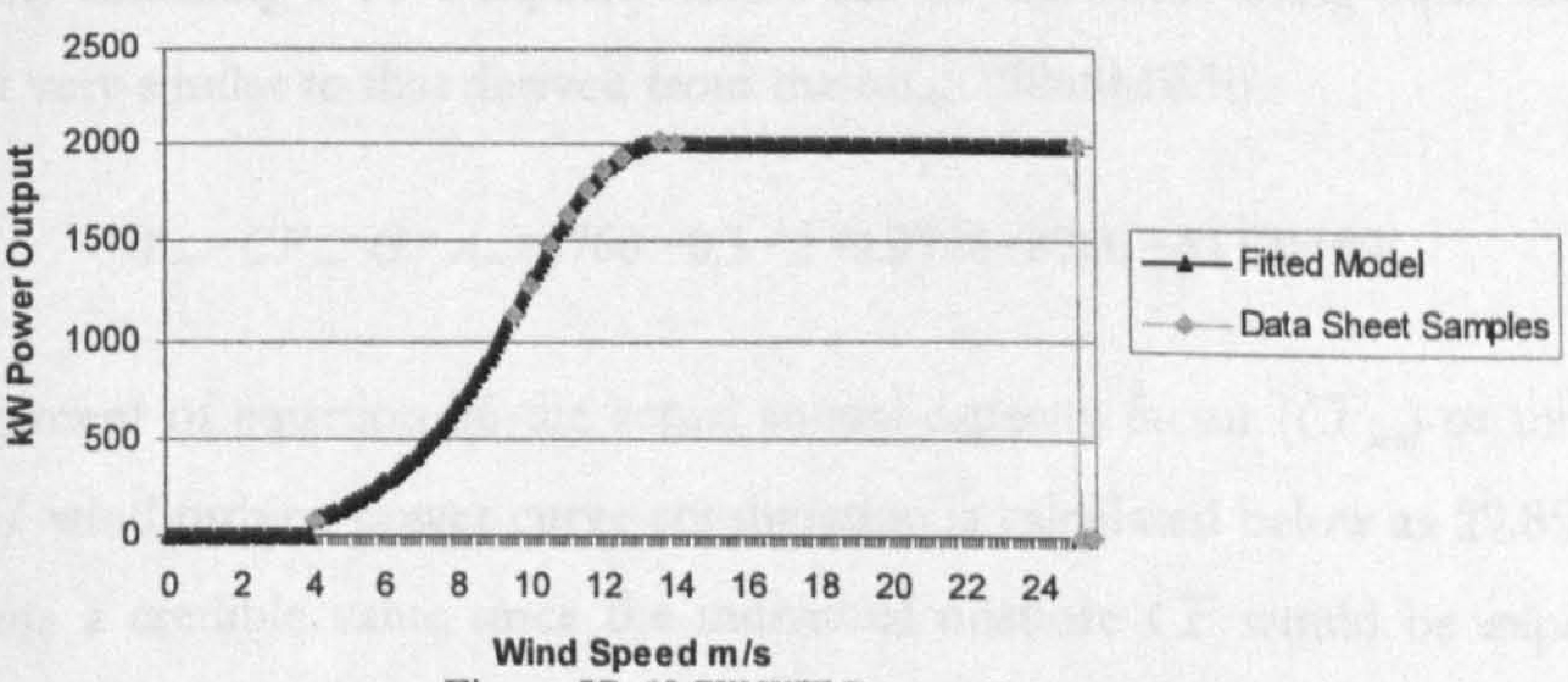

Figure 57: 2MW WT Power Curve

5.1.1 Model Validation Procedure

Previous chapters of this thesis have shown how the Markov model is fitted to annual reliability figures based on assumptions about downtime, maintenance policy and so on. However the other technical and economic model outputs have not yet been validated. To evaluate the other metrics of interest such as availability, yield and revenue, the first case study was conducted to confirm that the models produce credible outputs as compared with real or assumed figures.

Each run of the MCS comprised a 14,560 trial simulation after which average values were taken and stored in counters. This process was repeated 30 times and the statistical metrics in Table 35 are based on these 30 values extracted from each MCS.

Annual Metric		Annual Metric (Average)	σ^2	Upper *L*	Lower *L*
Availability (%)		97.26	0.54	97.46	97.06
Yield (MWh)		5068	35	5081	5055
Revenue (£/year)		308807	12337	313414	304201
Maintenance Freq. (actions/year)		2.000	NA	NA	NA
Failure Rates	Overall Turbine	1.054	0.150	1.110	0.998
	Gearbox	0.092	0.050	0.110	0.073
	Generator	0.109	0.041	0.124	0.094
	Blade	0.218	0.050	0.237	0.200
	E&E	0.635	0.114	0.677	0.593

Table 35: Validation of Models - Operational Metrical Obtained via MCS Model

The simulated availability of 97.26% from Table 35 is in line with perceived levels of availability in the industry, with 98% being typically quoted. The theoretical yield based on this availability assuming a 30% capacity factor can be calculated using equation 36, which gives a result very similar to that derived from the MCS (5068MWh).

$$Y_{ann} = CF_{ann} \times G \times A_{ann} \times 8760 = 0.3 \times 2 \times 0.9726 \times 8760 = 5112 MWh$$

By re-arrangement of equation 36 the actual annual capacity factor (CF_{ann}) of this particular wind profile/ wind turbine power curve combination is calculated below as 29.855%. Again, this represents a credible value since the individual onshore *CF* would be expected to be between 20% (badly placed wind turbine, poor wind resource or over-sized WT for site) to 35% (good placement, strong wind regime and optimally sized machine).

$$CF_{ann} = \frac{Y_{ann}}{G \times A_{ann} \times 8760} = \frac{5068}{0.9726 \times 2 \times 8760} = 29.855\%$$

Based on the yield from Table 35, the theoretical annual revenue R_{THEO} can be calculated in the case of no failures or repair costs (i.e. $C_{O\&M} = 0$). The difference between the MCS calculated revenue R_{MCS} (£308,807) and R_{THEO} (£385,152) if no failures occur is R_{DIFF} which corresponds to $C_{O\&M}$ for the MCS results.

$$R_{THEO} = MWh_{YEAR} \times (MP_{ROC} + MP_{ELEC}) = 5068 \times (40 + 36) = £385{,}152$$

$$R_{DIFF} = R_{THEO} - R_{MCS} = 385{,}152 - 308{,}807 = C_{O\&M} = £76{,}345$$

The annual O&M cost ($C_{O\&M}$) can be verified by analysing this difference between the theoretical revenue and model-generated revenue. There are two key cost components within $C_{O\&M}$ – reactive maintenance costs ($C_{REACTIVE}$) and preventive maintenance costs (C_{TBM}). These costs can be quantified to validate the operation of the models.

C_{TBM} can be broken down into labour and equipment hire costs (C_{LAB}, C_{EQ}), and the cost of preventive maintenance repairs ($C_{PREVENT}$). C_{LAB} and C_{EQ} are incurred twice per annum as a result of TBM, in addition to the repair cost incurred directly by TBM actions ($C_{PREVENT}$), resulting in the equation below.

$$C_{TBM} = 2 \times (C_{Eq} + C_{LAB}) + C_{PREVENT} = £5{,}400 + C_{PREVENT}$$

$C_{PREVENT}$ requires more information to fully quantify since it is based on the state of the Markov chain at the time of maintenance. For a MCS of the Markov chain, a maintenance frequency count can be produced which indicates which states were encountered in the time step before TBM is applied. The states of interest are 2-8 since these are the intermediate but functional states during which maintenance can be applied.

Since the MCS is run 30 times, each run comprising 364 x 20 x 2 trials, and clearly 364 represents the approximate number of days in a year, therefore the number of simulation 'years' is 30 x 20 x 2 = 1,200. Since TBM actions are every 6 months, this means the total number of TBM actions in the simulation period is approximately 2,400. Table 36 shows how the number of maintenance actions carried out in each intermediate state M is multiplied by the cost of repair to restore the system to the fully up state (C_r). This product is summed for each state (2-8) and the cost per TBM action is calculated as ~£14,989 which according to the bi-annual TBM policy results in annual costs of £29,979.

State	# Maintenance Actions, M	Cost of Repair, £ C_r	£ #M x C_r
2	29	10000	290000
3	69	5000	345000
4	5	15000	75000
5	1317	21000	27657000
6	148	26000	3848000
7	94	31000	2914000
8	11	36000	396000
		Sum	£35,525,000
		Cost per action	£14,989.45
		Bi-annual TBM, $C_{PREVENT}$	£29,979

Table 36: Annual TBM Repair Costs

The final element of O&M cost is repair and replacement costs after failure, $C_{REACTIVE}$. This is calculated on the basis of the simulated failure events and uses a modified version of equation 38, defined earlier in the thesis.

$$C_{REACTIVE} = \beta \cdot \lambda \times C_{CAP} + (1-\beta) \cdot \lambda \times \alpha \cdot C_{CAP}$$

The full calculation is shown in Table 37 which includes repairs and replacements conducted over the operational life of the components. The sum of $C_{REACTIVE}$ is calculated as £40,736.

Component	C_{CAP} £	λ_{MCS} Ann.	β Replace *pr*	$C_{CAP} \times \lambda \times \beta$ £	$1-\beta$ Repair *pr*	α Repair factor	$\alpha \times C_{CAP} \times \lambda \times (1-\beta)$ £
Gearbox	100000	0.092	0.6	5500	0.4	0.1	367
Generator	50000	0.109	0.6	3275	0.4	0.1	218
Rotor Blade	210000	0.218	0.6	27510	0.4	0.1	1834
E&E	5000	0.635	0.6	1905	0.4	0.1	127
			Sum	£38,190		Sum	£2,546

Table 37: Corrective Replacement & Repair Costs for MCS

Taking repair and replacement costs after failure, labour and equipment hire costs and TBM repair costs the full $C_{O\&M}$ is estimated in Table 38 and compared to the value obtained from the MCS. The difference between the two values is £230 which represents a very small difference in terms of the total $C_{O\&M}$.

The final stage of the model validation is to confirm that the annual failure rates are re-created accurately as in section 4.1.9. Figure 58 shows the values reproduced by the MCS simulation with individual confidence limits, which all fall within the range of the target probabilities. It is therefore demonstrated that the simulation program can successfully and accurately compute O&M costs as well as making adequate predictions of the other technical and economic metrics of interest. This means that other studies can be conducted with confidence in the models and meaningful conclusions drawn about wind farm condition monitoring techno-economic benefit.

$C_{O\&M}$ element – Annual	£
Repair and replacement cost after failure	40,736
Labour and equipment hire cost	5,400
TBM incurred repair cost	29,979
Total Manual $C_{O\&M}$	76,115
MCS $C_{O\&M}$	76,345
Difference	230

Table 38: Comparison of Manually Estimated and MCS Generated O&M Cost

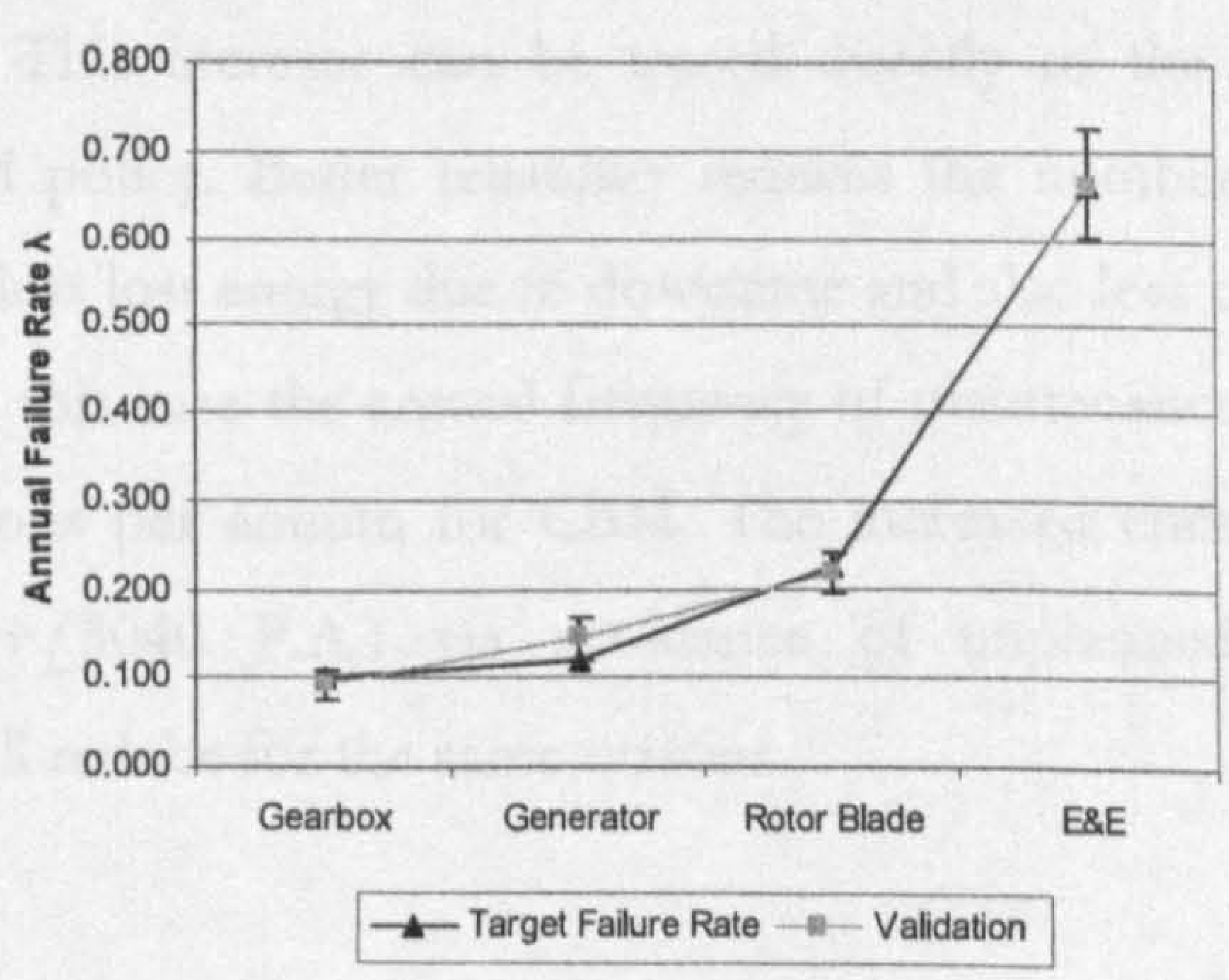

Figure 58: MCS Validation - Reliability with Confidence Limit

5.1.2 Onshore Wind Turbine Base Case Evaluation of Condition Monitoring Benefit

Having established that the model is valid, the first evaluation of condition monitoring benefit is conducted. The same input parameters are adopted for the base case as for model validation: component costs, failure probabilities and downtime durations are held constant (see section 5.1.1) while the model factors α and β are equal to 0.1 and 0.6 respectively.

In one set of results, TBM is applied in exactly the same way as for model validation. In the other set of results CBM is applied as explained in section 4.3.2 (CBM interval: High risk-15 days, medium risk-15 days and low risk-100 days). The summary results table for the two maintenance policies is shown in Table 39.

Annual Metric		TBM	CBM
Availability (%)		97.26	97.94
Yield (MWh)		5068	5108
Revenue (£)		308807	316095
Maintenance Freq. (actions/year)		2.000	1.800
Failure Rates	Overall Turbine	1.054	0.9308
	Gearbox	0.092	0.0250
	Generator	0.109	0.0767
	Rotor Blade	0.218	0.1800
	E&E	0.635	0.6492
Lost Energy MWh (MWh/year)		137.275	97.03

Table 39: Onshore Base Case Evaluation of TBM & CBM

The technical impact of CBM compared with TBM is that the annual availability the WT increases by 0.68%. This increase can be traced directly to the reliability improvement induced by the CBM policy. Better reliability reduces the number of unplanned outages, which in turn means less lost energy due to downtime and also less component replacements are required. Also, in this case the annual frequency of maintenance reduces from 2 actions for TBM to 1.8 actions per annum for CBM. The increased energy yield corresponds to extra revenue of (+£3040 P.A.) via avoidance of unplanned outages and reactive maintenance costs will reduce for the same reasons.

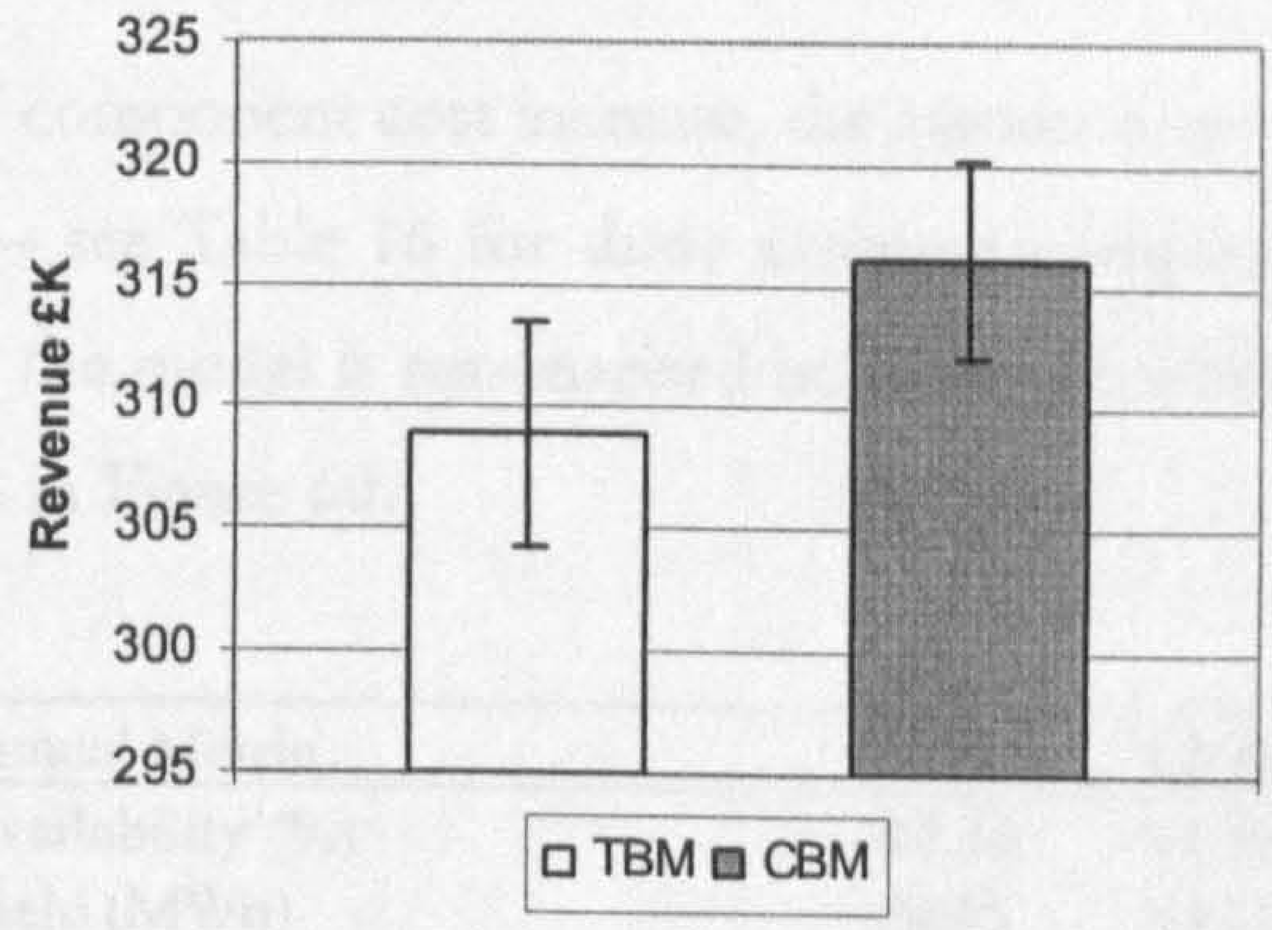

Figure 59: Onshore Base Case Revenue Comparison of TBM & CBM

The economic performance of the two maintenance policies for the base case is shown in Figure 59. The CBM policy has a net benefit of £7,288 per WT per annum: however care must be taken interpreting the result. Firstly, the overlapping confidence limits for TBM and CBM show that there is significant uncertainty. Other main caveats at this stage are that the CM system is assumed to be 100% accurate in identifying failures, and that incurred cost per CBM action is fairly modest (cost of repair + labour + equipment hire). This means that CBM actions do not require component replacements. Also the example provided in the base case allows CBM actions to be carried out as early as 15 days after detection, which may not be long enough to source the necessary parts or specialised equipment.

The base case demonstrates technical and economic benefits of CBM relative to TBM. However, this result is valid only for this particular combination of reliability figures, downtime estimates and model cost parameters. Clearly more detailed analyses are needed to explore these issues further and, in each case, to establish if a link exists to the techno-economic success of WT CM systems.

5.1.3 Increased Component Costs

One of the current key issues in wind turbine O&M is the increasing cost of components, which is brought about by worldwide bottlenecks in WT manufacture. Until now the component costs have been based on assumptions in McMillan and Ault (2008) – see Table 21 for details.

To examine the effect of component cost increase, the assumptions of Sterzinger and Svrcek (2004 p53) are adopted – see Table 16 for these assumed component costs. The effect on the metrics generated by the model is summarised in Table 40, while the revenue impact for TBM and CBM is shown in Figure 60.

	Annual Metric	TBM	CBM
	Availability (%)	97.16	97.99
	Yield (MWh)	5065	5114
	Revenue (£/year)	246968	264476
	Maintenance Freq. (actions/year)	2.000	1.773
Failure Rates	Overall Turbine	1.1083	0.9367
	Gearbox	0.1058	0.0283
	Generator	0.1258	0.0642
	Rotor Blade	0.2108	0.1942
	E&E	0.6658	0.6500
	Lost Energy MWh (MWh/year)	140.379	91.42

Table 40: Onshore Evaluation of TBM & CBM using Increased Component Costs

The net benefit of the CBM policy is £17,508 which is over double the level calculated in the base case in section 5.1.2. This is intuitive as it suggests that higher component costs strengthen the case for CM deployment, increasing the economic consequences of an unplanned outage. Furthermore, another effect of increased component costs is to drive up the magnitude of the confidence limits in Figure 60. Finally, comparing the revenue streams of the base case (see Table 39) with increased component costs reveals that the revenues are reduced by around 20% if component costs are significantly increased.

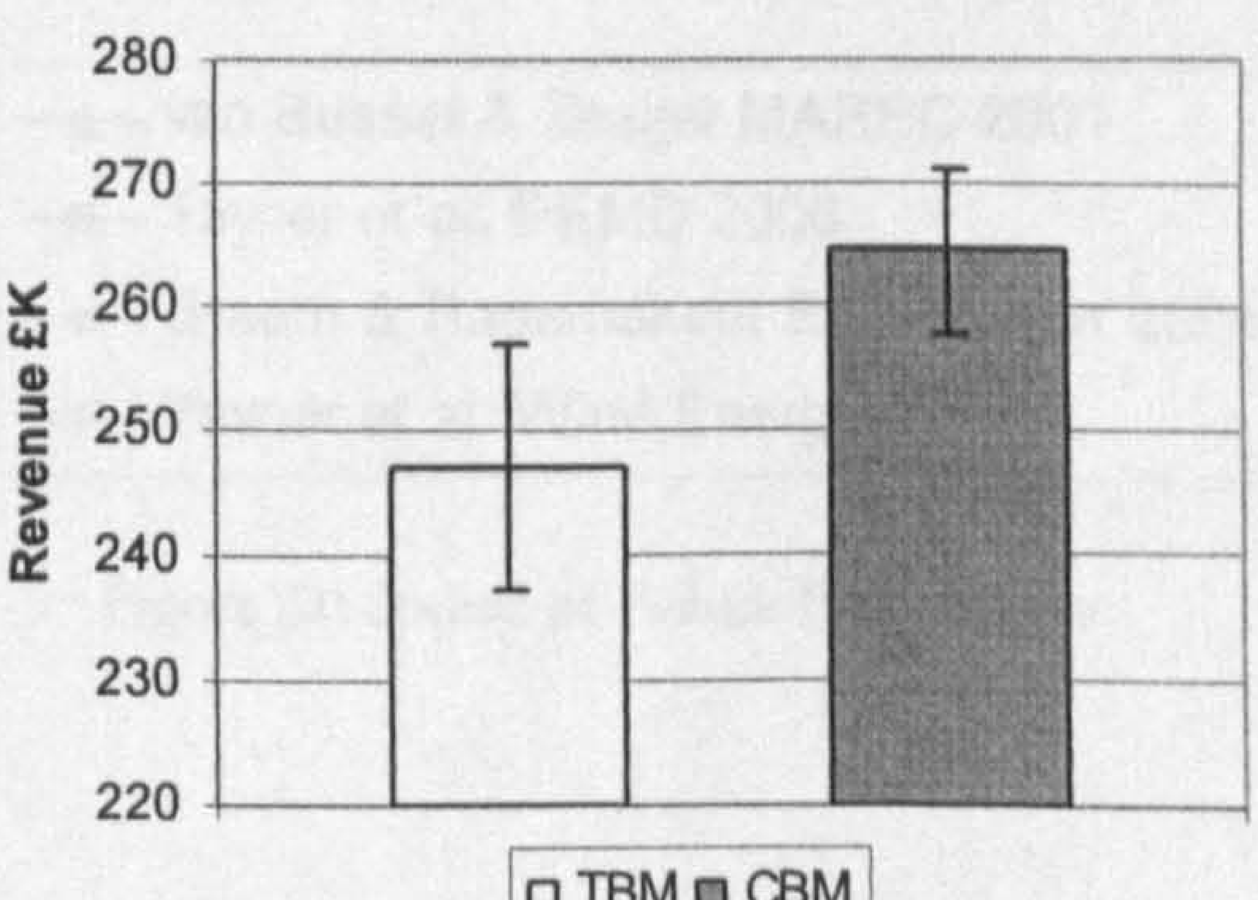

Figure 60: Revenue Comparison of TBM & CBM using Increased Component Costs

5.1.4 Onshore Wind Turbine Base Case Sensitivity to Component Reliability Levels

Mention has been made of the various available sources of WT component reliability data. A representative set of these data is shown in Figure 61, illustrating the significant spread of possible values. If the extreme high, low and median values from these studies are plotted, a 'reliability envelope' can be calculated which represents a spread of credible reliability values, as shown in Figure 62. This range of values can be used to establish the influence of reliability on CM benefit.

The model fitting procedure outlined in section 4.1.9 is applied using the three sets of reliability figures derived from Figure 62. When these have been fitted it is possible to establish the level of sensitivity of CM benefit relative to this component reliability envelope.

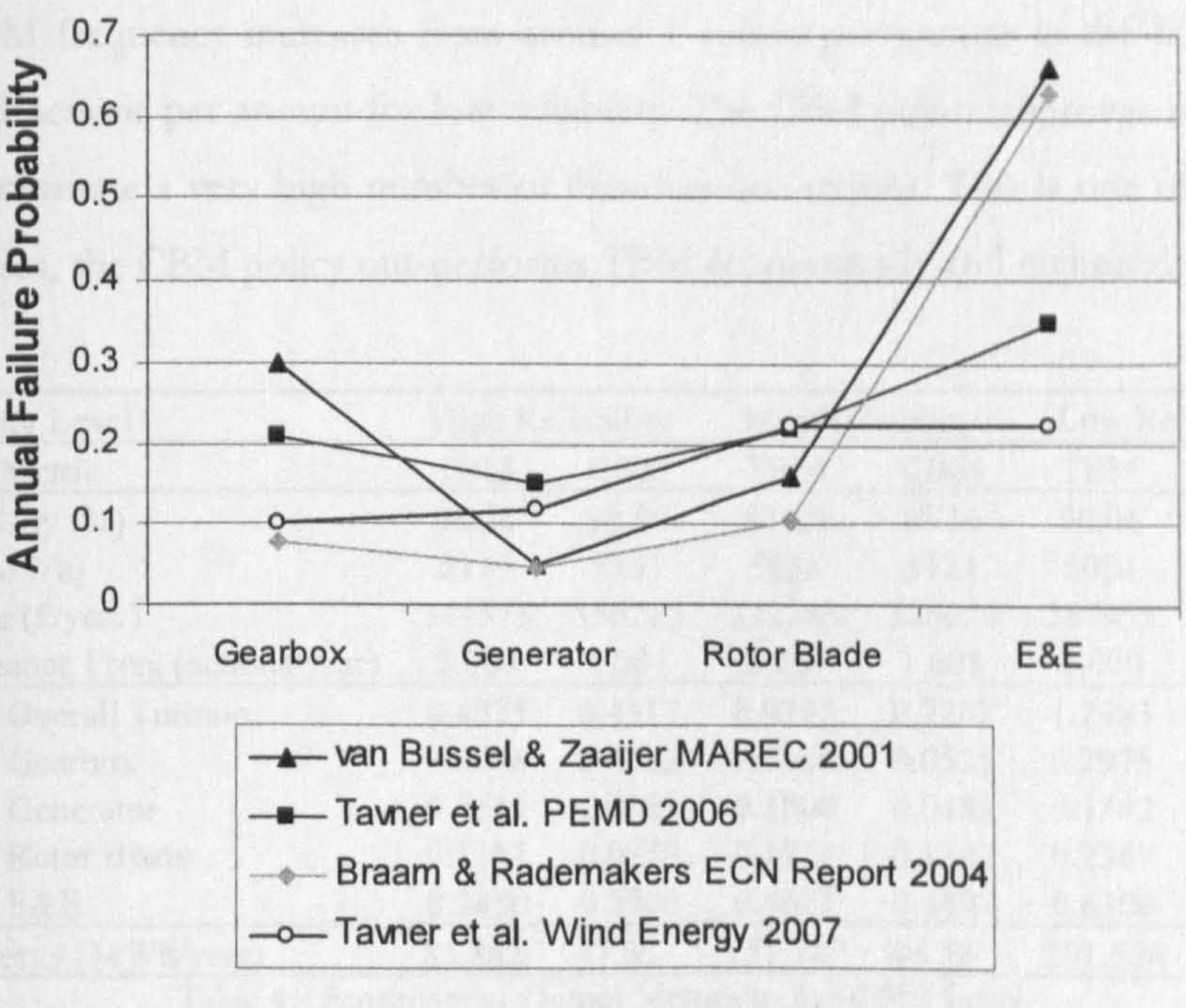

Figure 61: Spread of Failure Probabilities

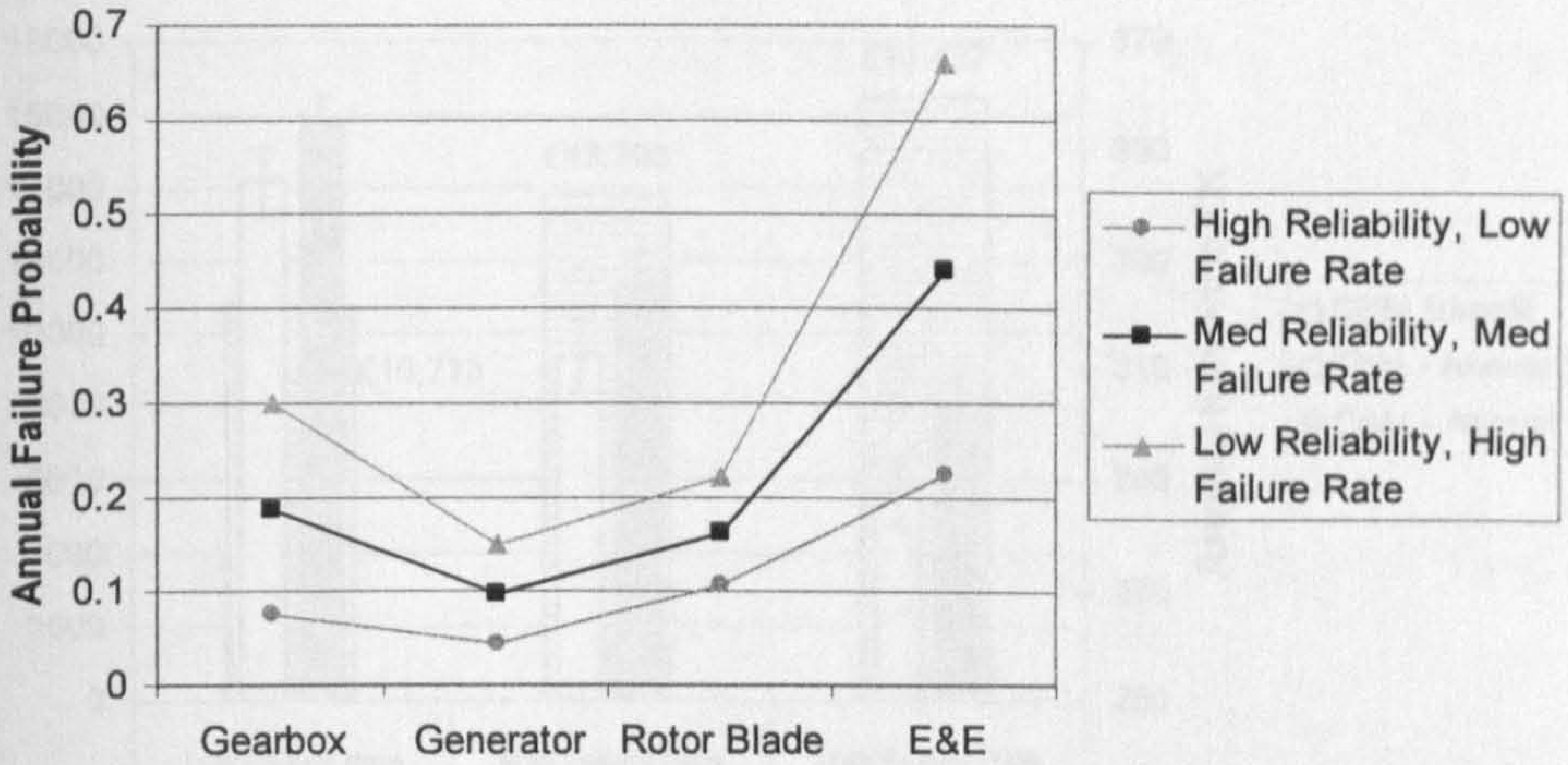

Figure 62: Wind Turbine Reliability Performance Envelope

Table 41 summarises the results from the various MCS. The general effect of reduction in reliability is to reduce availability, energy yield, and revenues, while lost energy increases. Average CBM frequency increases from around 1 action per annum in the high reliability case to 2.091 actions per annum for low reliability. The CBM policy improves reliability, but does not necessitate a very high number of maintenance actions. This is one of the reasons that in all cases, the CBM policy out-performs TBM economically and technically.

Reliability Level		High Reliability		Med Reliability		Low Reliability	
Annual Metric		TBM	CBM	TBM	CBM	TBM	CBM
Availability (%)		98.24	98.96	97.00	98.16	96.06	97.60
Yield (MWh)		5119	5157	5053	5121	5004	5093
Revenue (£/year)		344575	355288	312283	326076	287455	303892
Maintenance Freq. (actions/year)		2.000	1.001	2.000	1.608	2.000	2.091
Failure Rates	Overall Turbine	0.4975	0.4317	0.9292	0.7242	1.2983	1.0183
	Gearbox	0.0708	0.0183	0.1950	0.0525	0.2975	0.0600
	Generator	0.0633	0.0483	0.1000	0.0483	0.1342	0.0875
	Rotor Blade	0.1183	0.0950	0.1717	0.1342	0.2367	0.1883
	E&E	0.2450	0.2700	0.4625	0.4892	0.6300	0.6825
Lost Energy (MWh/year)		85.882	47.95	151.787	84.50	201.504	112.44

Table 41: Sensitivity of Output Metrics to Reliability Level

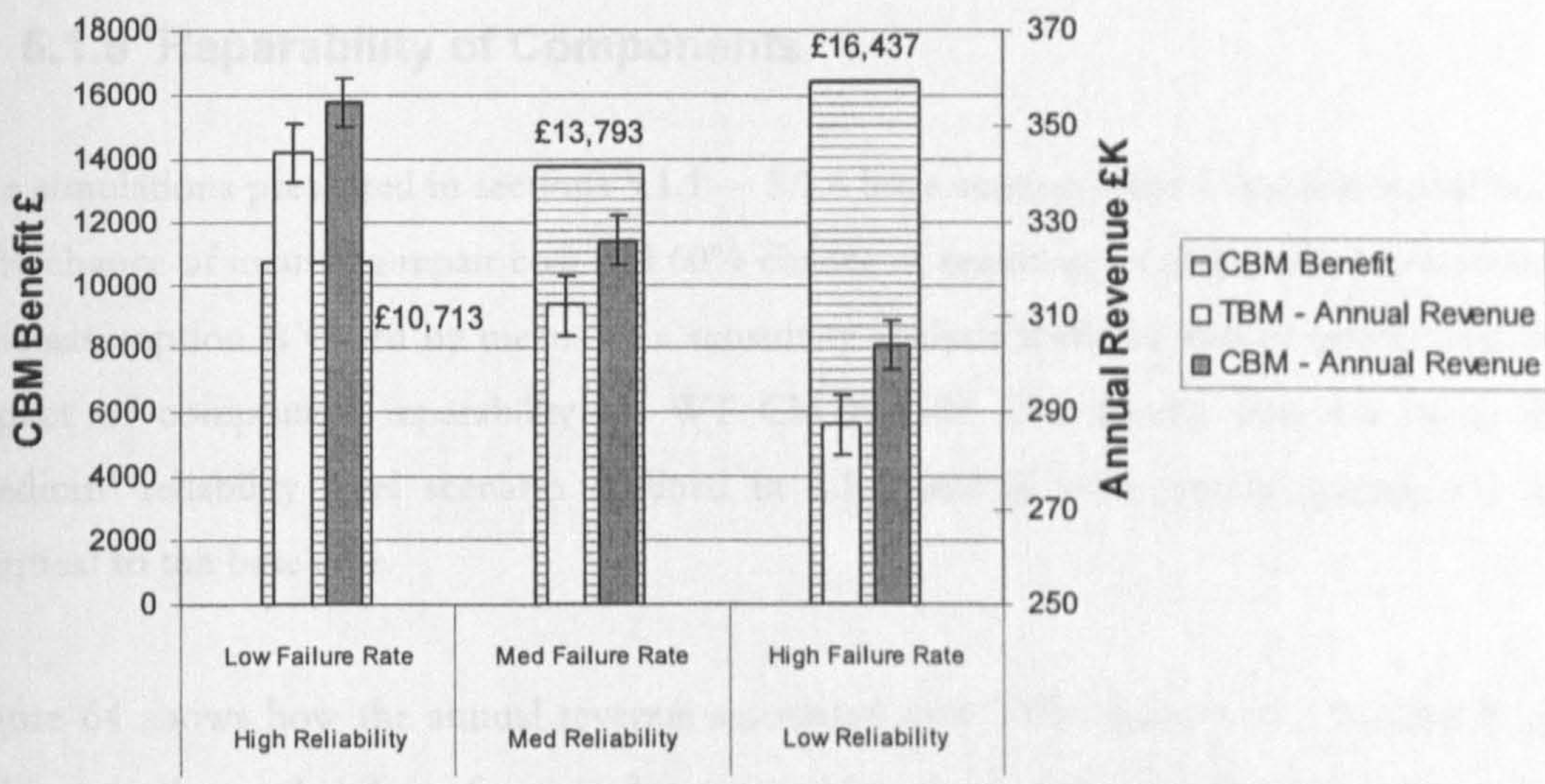

Figure 63: Revenues and CM Benefit with Decreasing Reliability

Figure 63 shows the annual CM benefit (CBM Revenue-TBM revenue) as a function of the reliability level, giving increasing benefit levels of £10,713, £13,793 and £16,437 with reducing reliability. The revenue on adoption of both maintenance policies is clearly coupled with reliability, and some coupling between reliability level and CM benefit is observed for these onshore techno-economic conditions.

In conclusion, these results indicate that for the range of reliability levels examined, CBM benefit increases as WT reliability decreases.

5.1.5 Reparability of Components

The simulations presented in sections 5.1.1 – 5.1.4 have assumed that a reactive repair has a 40% chance of incurring repair cost and 60% chance of requiring a component replacement. This assumption is varied by means of a sensitivity analysis with the aim of quantifying the impact of component reparability on WT CM benefit. The model was run using the 'medium' reliability level scenario outlined in 5.1.4 and all other model parameters are identical to the base case.

Figure 64 shows how the annual revenue associated with TBM reduces in a broadly linear fashion as the probability of repair decreases. Also clear in this diagram is that a CBM strategy is not as strongly coupled with repair probability. A possible hypothesis to explain this is that the reliability has been increased by the CBM policy to the point where the proportion of reactive maintenance is very small compared with condition-based maintenance. Therefore the system maintained according to a CBM policy is largely shielded from the effects of reparability variation.

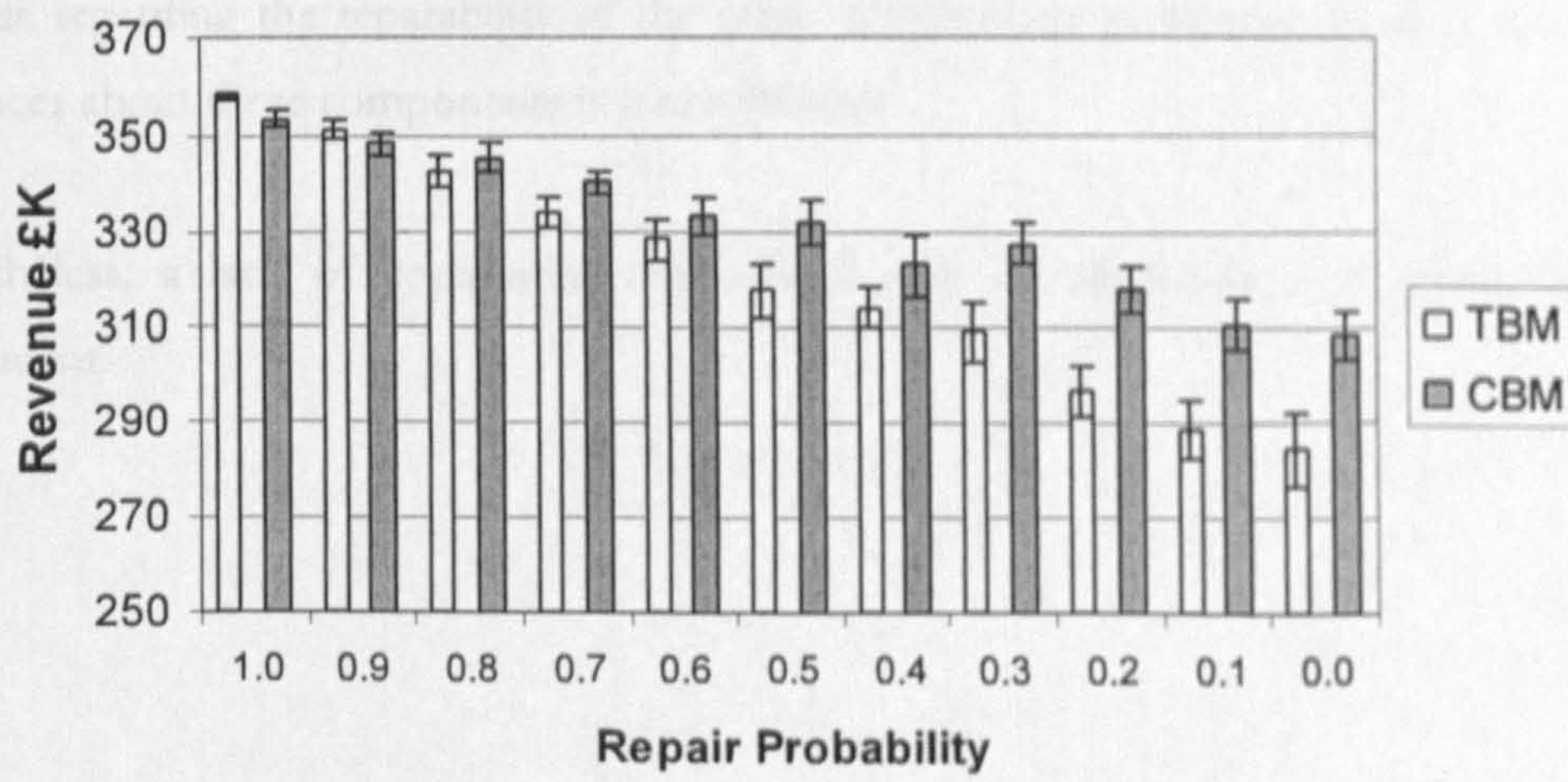

Figure 64: Revenue Impact of WT Component Reparability

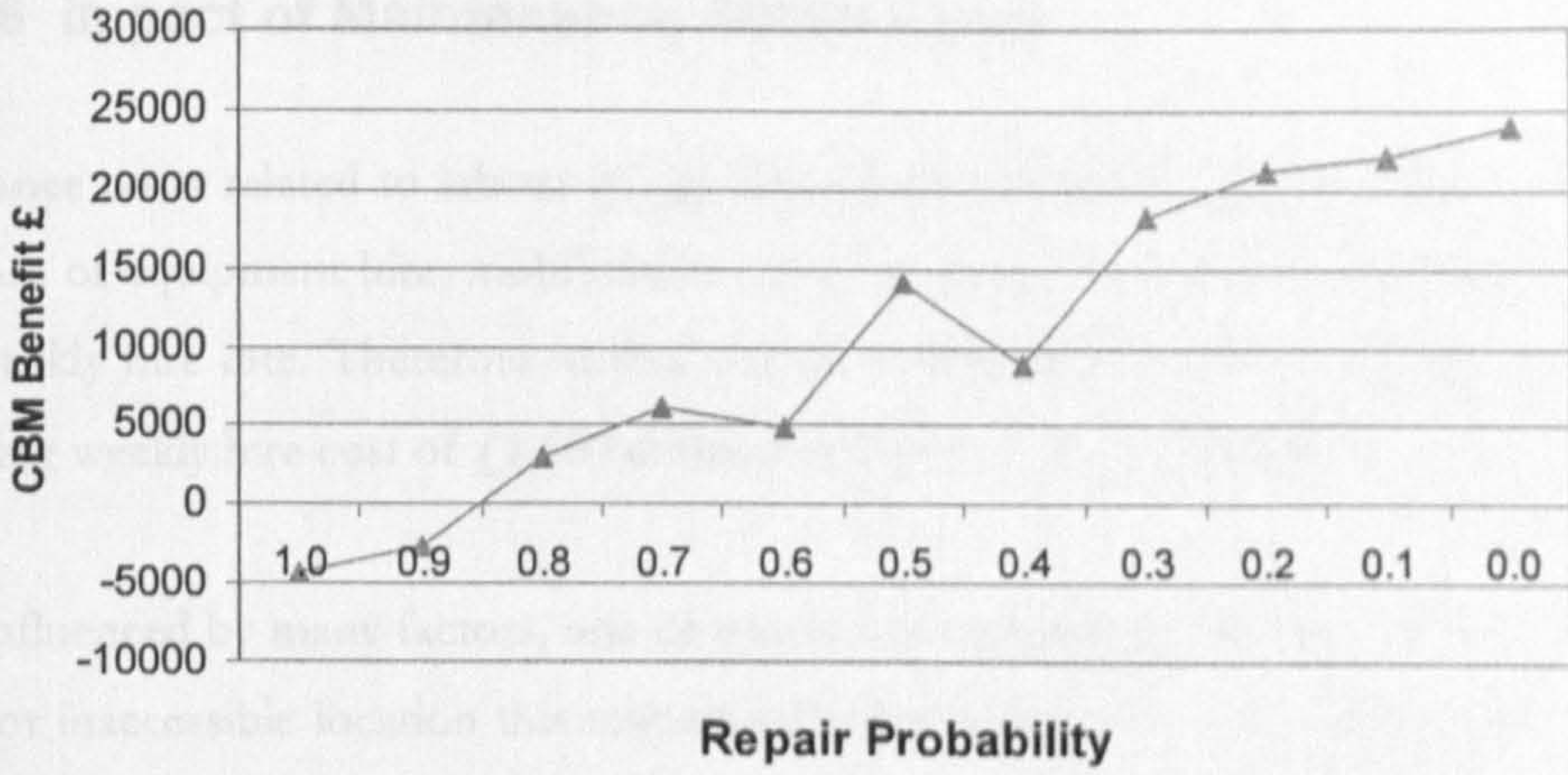

Figure 65: CM Benefit as a Function of Component Reparability

The effect of varying the repair probability on CBM benefit is shown in Figure 65. This illustrates that if the probability of repair is 0.9 (90%) or higher, then TBM is more cost-effective than CBM. This is interesting since it is by no means impossible that a component could be repaired in 90% of cases. On the other hand, data from Nilsson and Bertling (2007) suggests a repair probability of around 40% for gearboxes, which would have to alter considerably for TBM to be more cost-effective than CBM. On the other hand, no data is available regarding the reparability of the other components (generator, blades) so making inferences about these components is more difficult.

Nevertheless, a lack of component reparability may be identified as a driver for CM deployment.

5.1.6 Impact of Maintenance Action Costs

Maintenance costs related to labour (C_{LAB}) and equipment hire (C_{EQ}) are subject to change. In the case of equipment hire, mobilisation costs for crane hire can be a significant addition to the weekly hire rate. Therefore in this section a mobilisation cost of £1,500 is added to the existing weekly hire cost of £1,500 defined in Table 17 (C_{EQ} =£3,000).

C_{LAB} is influenced by many factors, one of which is accessibility of the site. If the site is in an isolated or inaccessible location this may be reflected in a premium for labour. Additionally, a lack of availability of suitably skilled maintenance workers could drive C_{LAB} upwards. Therefore a factor of 1.5 as applied (C_{LAB} =£1,800) in order to examine the effect of such drivers. Figure 66 shows that the impact of the increased maintenance costs as a function of decreasing reliability level (CBM benefit reduces from £18,438 to £14,882 to £6,552).

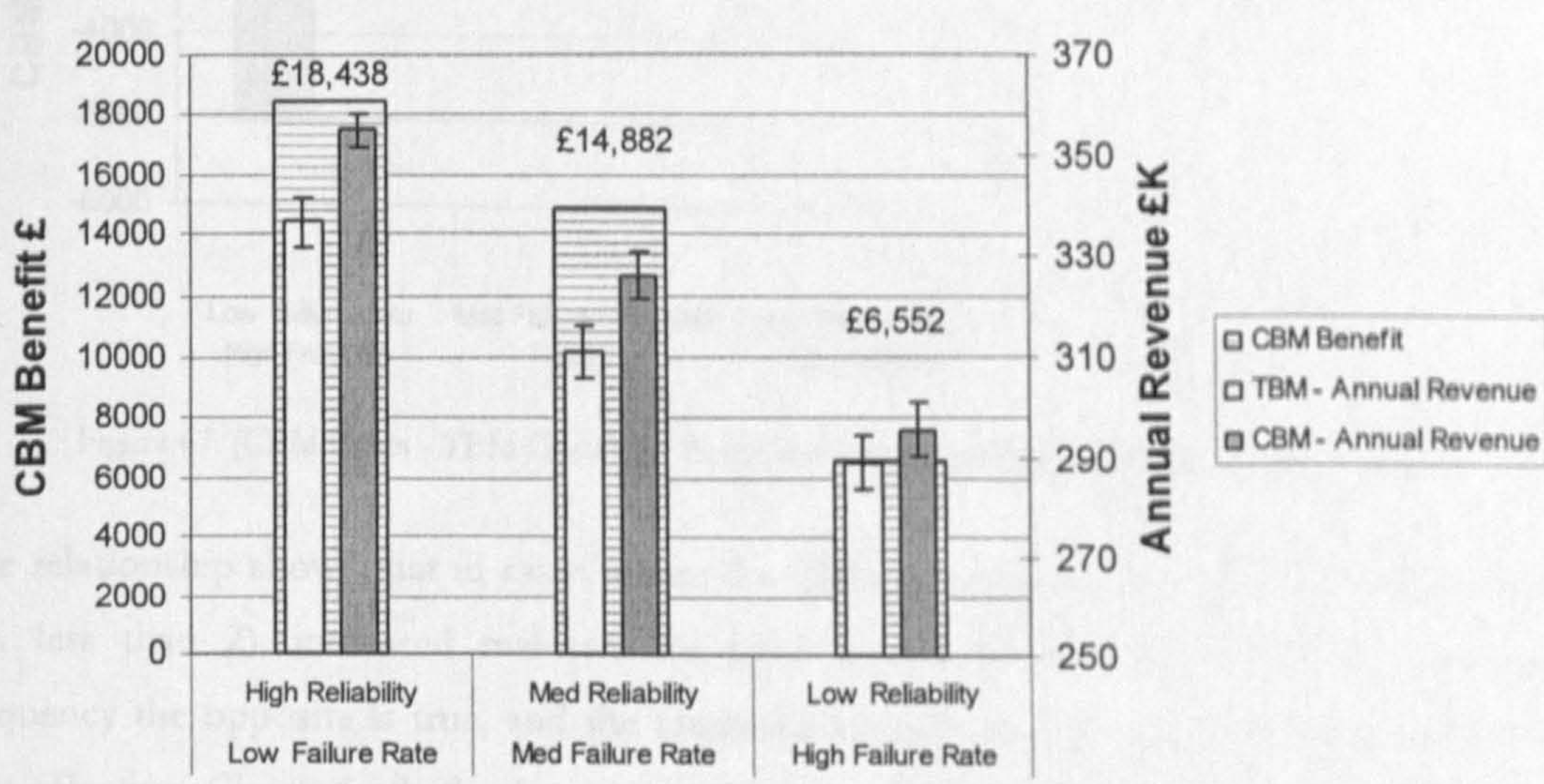

Figure 66: TBM & CBM Revenue under Increased Maintenance Costs

Figure 66 clearly shows that as reliability decreases, the effect is to reduce the CBM benefit. This is because the CBM actions become more frequent and therefore the cost is more significant as the number of failures increases – similar to the base case. However, the effects are slightly different. For example, in the high reliability case the CBM benefit actually increases compared with the base case despite the increased maintenance cost. Conversely, the CBM benefit in the low reliability case is much smaller (£6,552) than the base case (£16,437).

These effects are investigated by comparing the difference between condition based and time based incurred maintenance costs for both base case maintenance costs and increased maintenance costs evaluated in this section (see Figure 67).

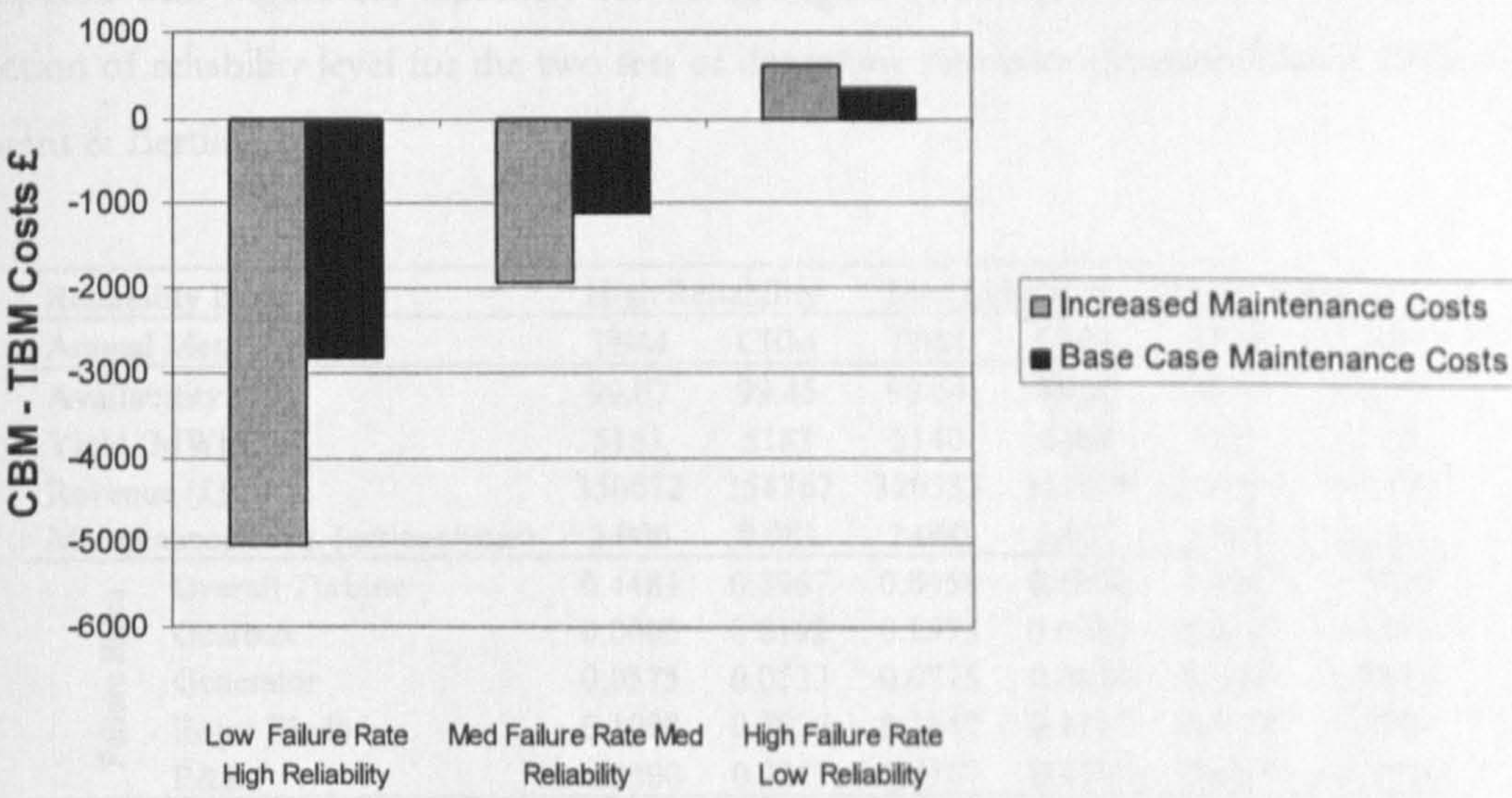

Figure 67: (CBM Costs - TBM Costs) for Base Case and Increased Maintenance Cost Scenario

The relationship shows that in cases where the CBM frequency is less than TBM frequency (i.e. less than 2), increased maintenance costs boost the case for CBM. Beyond this frequency the opposite is true, and the increased maintenance costs act to make CBM less cost-effective. Clearly both the frequency and cost of CBM actions are key in determining the economic case for WT CM. In particular, Figure 67 and Figure 66 suggest that high reliability conditions in tandem with high cost of maintenance actions enable highly economic WT CBM.

5.1.7 Impact of Downtime Variation

Until now, the downtime values have been those suggested by the industrial research partner ('Scottish Power 2005'). The system is now tested using the downtime assumptions derived by Ribrant & Bertling (2007) – see Figure 28. Therefore the downtime for gearbox, generator, rotor blade and E&E decreases to 11, 9, 4 and 1 day(s) respectively. Table 42 summarises the techno-economic metrics generated when these reduced downtimes are simulated in the model. The positive impact on availability and lost energy is clear when compared with Figure 63, especially for TBM. Figure 68 compares the CBM benefit as a function of reliability level for the two sets of downtime estimates (Scottish Power 2005 and Ribrant & Bertling 2007).

Reliability Level		High Reliability		Med Reliability		Low Reliability	
Annual Metric		TBM	CBM	TBM	CBM	TBM	CBM
Availability (%)		99.07	99.45	98.64	99.10	98.12	98.73
Yield (MWh)		5163	5183	5140	5169	5111	5154
Revenue (£)		350672	354767	320335	331678	287353	305093
Maintenance Freq. (actions/year)		2.000	0.981	2.000	1.637	2.000	2.181
Failure Rates	Overall Turbine	0.4483	0.3967	0.8958	0.6950	1.4067	1.0283
	Gearbox	0.0600	0.0192	0.1975	0.0433	0.3208	0.0858
	Generator	0.0575	0.0533	0.0775	0.0650	0.1600	0.0842
	Rotor Blade	0.1008	0.1025	0.1642	0.1317	0.2658	0.1900
	E&E	0.2300	0.2217	0.4567	0.4550	0.6600	0.6683
Lost Energy (MWh/year)		41.886	21.86	65.339	36.13	94.080	50.86

Table 42: TBM & CBM Metrics for Decreased Downtimes (Ribrant & Bertling, 2007)

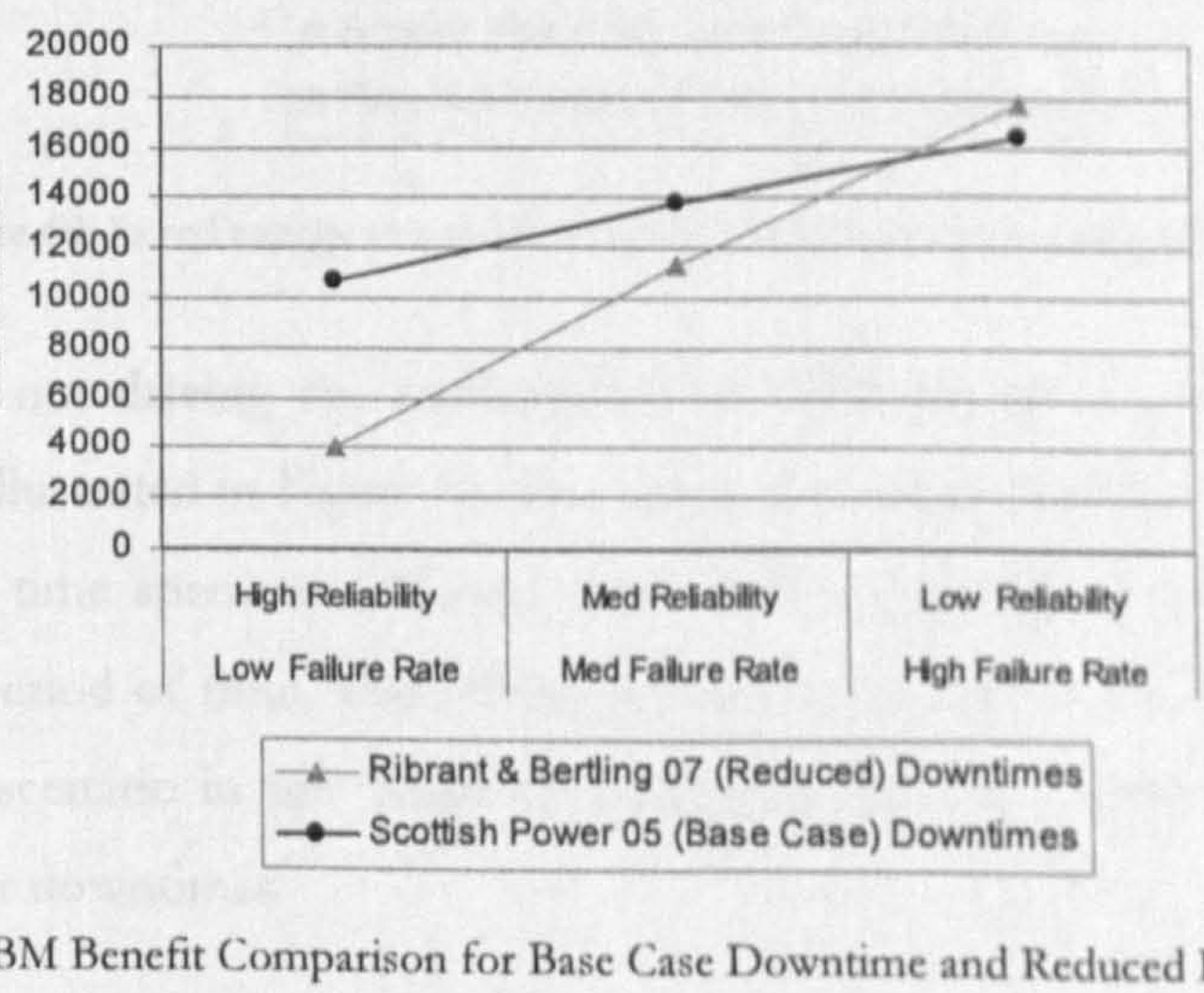

Figure 68: CBM Benefit Comparison for Base Case Downtime and Reduced Downtime

The results show that CM benefit for lower downtime is significantly reduced in the case of high reliability and marginally reduced for medium reliability cases: however it increases slightly for low reliability. This indicates that the effect of downtime reduction is to increase the coupling between CBM benefit and reliability level, which can be observed in Figure 68 by the steeper slope of the trace of 'reduced downtimes'.

This is a counter-intuitive result since reduced downtime decreases the significance of unplanned outages, which in a real situation means that the operator does not have to place such a high importance on outage avoidance. To illustrate this, consider Figure 69 which is a plot of saved energy as a result of CBM for both downtime estimates. Since the base case downtime scenario saves more energy with decreasing reliability, this should act to create divergence the two traces in Figure 68, however they instead converge.

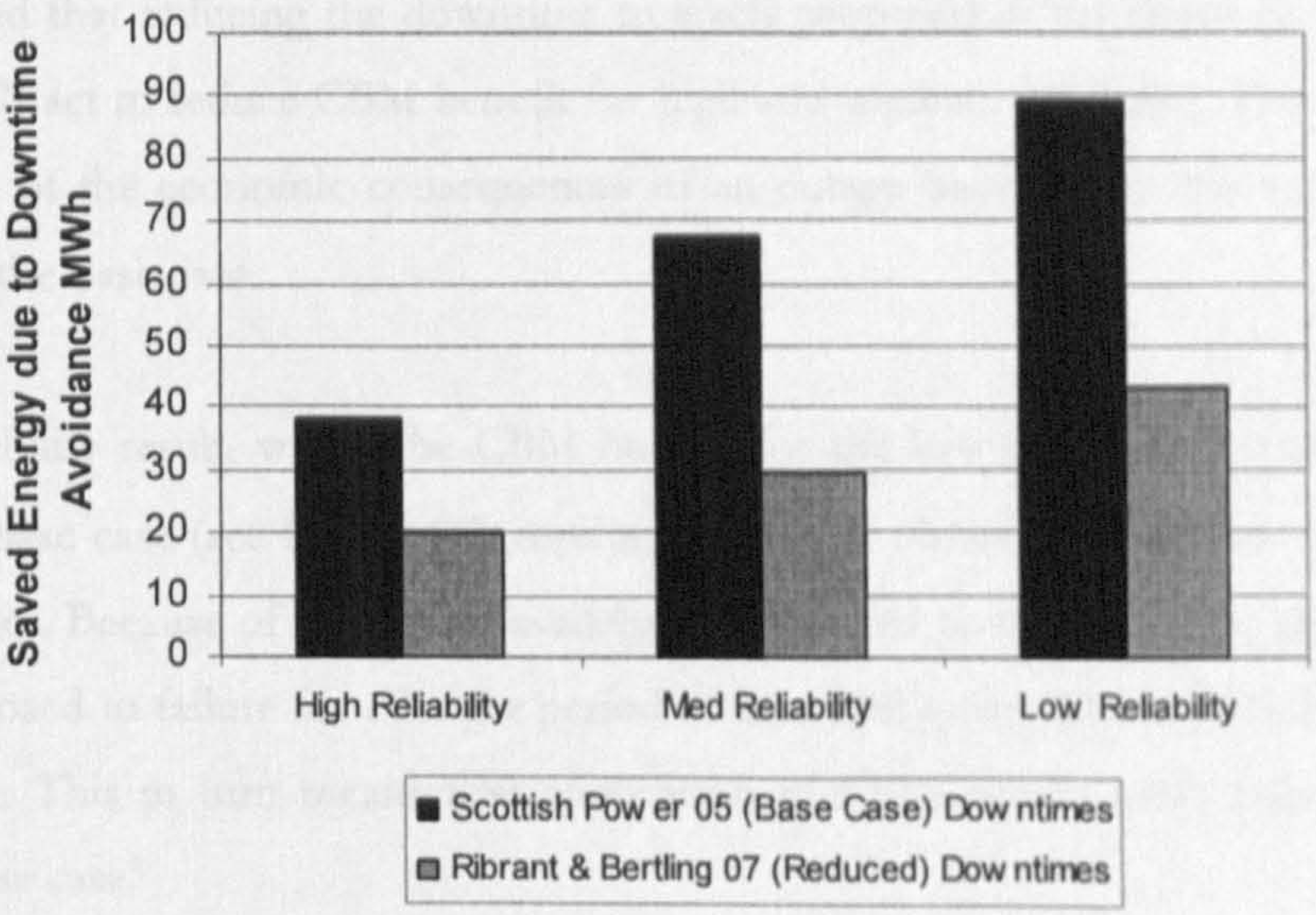

Figure 69: Saved energy as a result of CBM for 2 Downtime Estimates

Clearly downtime is not driving the convergence of CBM benefit for the base case and reduced downtimes illustrated in Figure 68. It is noted that lower downtime results in higher WT availability (less time spent in a 'down' state). Hence the system will be 'exposed' to failure for a longer period of time. The effects of this can be appreciated by comparing the low reliability TBM scenario in the 'reliability sensitivity' base case and those calculated in this section, for lower downtimes.

TBM Annual Metric Thesis Section	Low Reliability, Base Case 5.1.4	Low Reliability, Reduced Downtime 5.1.7 (current section)	Increase
Availability (%)	96.06	98.12	+2.14%
Gearbox Failure Rate	0.2975	0.3208	+7.83%
Generator Failure Rate	0.1342	0.1600	+19.23%
Rotor Blade Failure Rate	0.2367	0.2658	+12.29%

A side-effect of the improvement in availability (as a result of reduced downtimes) is to drive up the failure rates of the components. The gearbox, generator and rotor blade failure rates increase by 7.83%, 19.23% and 12.29% respectively for the low downtime scenario. Since CBM benefit is calculated as $(£R_{CBM}-£R_{TBM})$, this means that the scope for improving the failure rates in the low downtime scenario is larger than for the base case. This is why the CBM benefit is surprisingly high for the low reliability, low downtime scenario in Figure 68.

It is concluded that reducing the downtime to levels proposed in the paper by Ribrant and Bertling (2007) act to reduce CBM benefit for high and medium reliability. This is driven by the reduction of the economic consequences of an outage because the lost energy is small compared to the base case.

The low reliability result, where the CBM benefit for the low downtime scenario is larger than for the base case (see Figure 68), results from a less obvious consequence of reducing WT downtimes. Because of the higher availability compared to the base case, this means the system is exposed to failure for a longer period of time and more failures will occur than for the base case. This in turn means that application of CBM avoids more failures than the equivalent base case.

5.1.8 Impact of Wind Regime

The site wind regime has clear implications for the energy yield at a wind farm site: however it is unclear how the strength of the wind profile could affect the case for CM. Therefore the base case presented in section 5.1.2 is taken and a stronger wind profile is used, corresponding to conditions found in exposed coastal areas such as the Shetland Isles of Scotland. The base case wind profile has a mean wind speed of 6.95m/s whereas the increased profile used in this section has a mean of 7.95m/s.

The impact of the different wind profiles are summarised in Table 43. As expected, the yield, revenue and lost energy all increase as a result of the stronger wind profile. The CBM benefit is reduced compared to the base case – CBM benefit is £3,759 for the high wind profile, compared with £7,288 for the base case wind profile. However this difference is probably too small to be considered significant because the confidence limits are of the same order as the difference in CBM benefit (see confidence limits in Figure 59).

Wind Regime		Base Case Wind Profile 6.95m/s		High Wind Profile 7.95m/s	
Annual Metric		TBM	CBM	TBM	CBM
Availability (%)		97.26	97.94	97.12	97.73
Yield (MWh)		5068	5108	6660	6714
Revenue (£/year)		308807	316095	429029	432788
Maintenance Freq. (actions/year)		2.000	1.800	2.000	1.802
Failure Rates	Overall Turbine	1.0542	0.9308	1.0800	0.9792
	Gearbox	0.0917	0.0250	0.1033	0.0267
	Generator	0.1092	0.0767	0.1217	0.0825
	Rotor Blade	0.2183	0.1800	0.2158	0.2033
	E&E	0.6350	0.6492	0.6392	0.6667
Lost Energy (MWh/year)		137.275	97.03	190.505	136.88

Table 43: Summary of TBM & CBM Metrics for Different Wind Regimes

Figure 70 illustrates how the CBM benefit for the two wind profiles changes with respect to reliability level. The comparison of these results is particularly interesting. For the base case wind profile (mean = 6.95m/s), the CBM benefit increases with decreasing reliability, as was shown in 5.1.4. Similarly, the stronger wind profile evaluated in this section (mean = 7.95m/s) has the effect of accelerating this trend: the CBM benefit increases with decreasing reliability, but with more pronounced effects at low reliability.

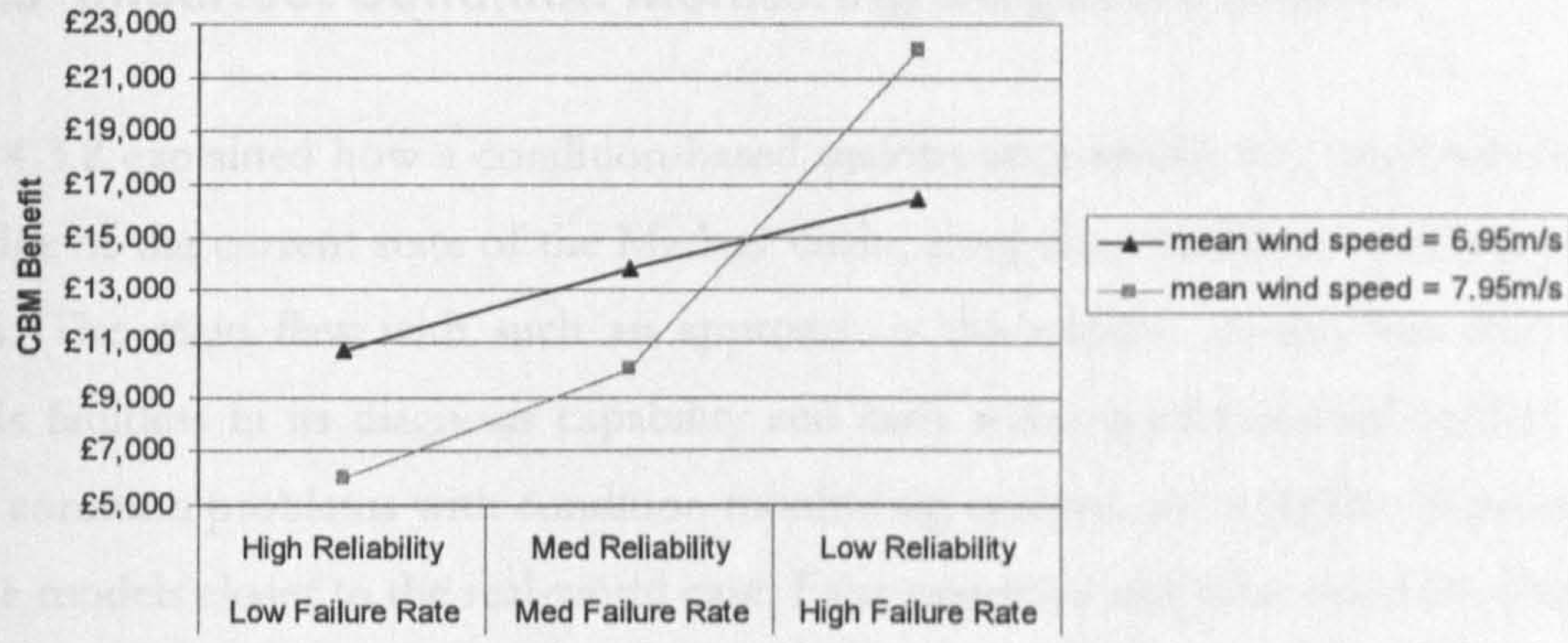

Figure 70: CBM Benefit for a Range of Reliability Levels & Two Wind Profiles

Not only does the stronger wind profile act to increase CBM benefit, but this benefit increases as the system becomes less reliable. The reason for this can be appreciated by observing Figure 71, which shows the saved energy revenue due to avoidance of outages (acts to increase CBM benefit) minus the incurred cost of CBM actions (acts to decrease CBM benefit).

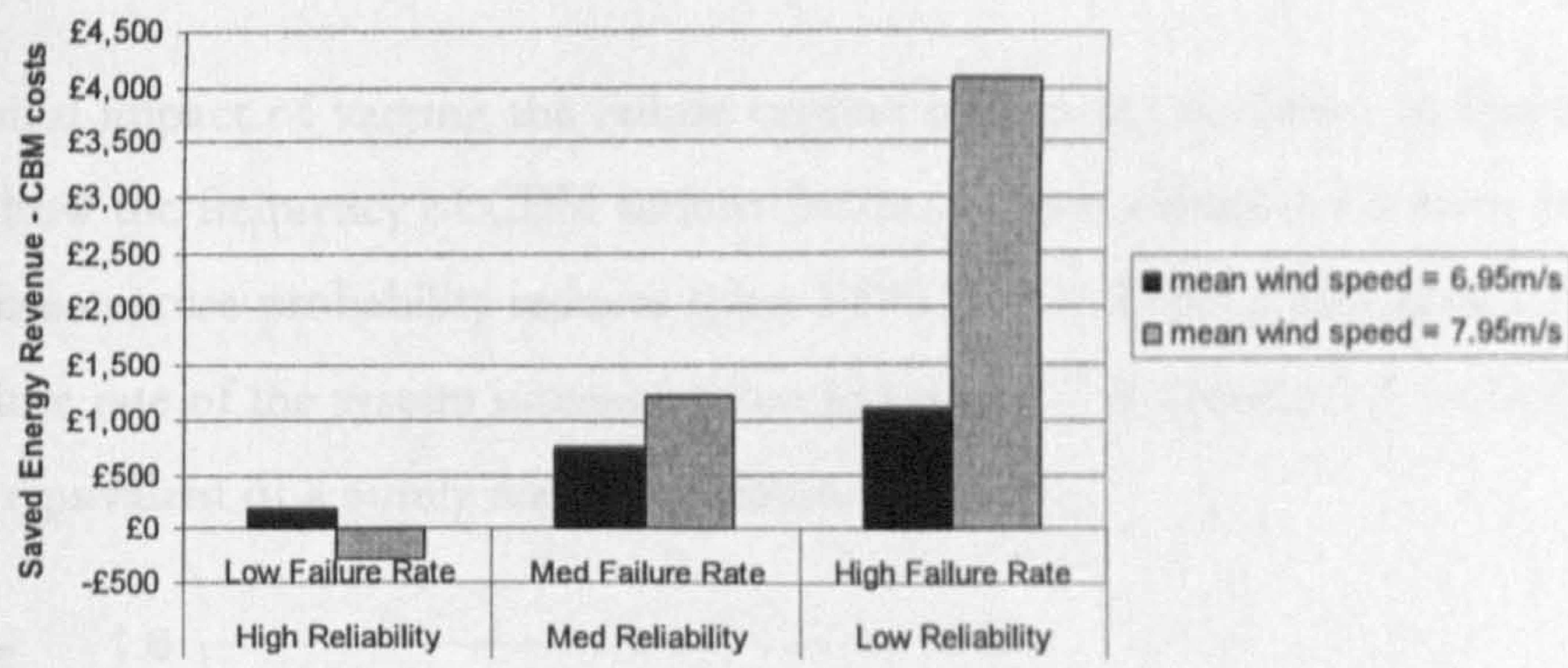

Figure 71: CBM Saved Energy Revenue minus Incurred CBM Costs

The balance of these two elements broadly mirrors the trends observed in Figure 70. It can be seen that for the case of the stronger wind profile (mean=7.95m/s), the positive difference between saved energy revenue (i.e. $R_{LOST,\ TBM} - R_{LOST,\ CBM}$) and incurred CBM cost (CBM frequency x (C_{EQ}+C_{LAB})) is increasing, while in the case of the base case profile (mean=6.95m/s) the increase is less marked. This effect is driving the result in Figure 70 and shows the importance of the balance between cost of maintenance actions and positive economic benefits of CBM. This implies that there is a stronger economic case for deployment of CM at high wind sites, especially if reliability is low.

5.1.9 Imperfect Condition Monitoring Diagnosis Impact

Section 4.3.2 explained how a condition-based maintenance model was implemented based knowledge of the current state of the Markov chain, alongside condition-based maintenance intervals. The main flaw with such an approach is the implied assumption that the CM system is faultless in its diagnosis capability and early warning of potential failures. In this section, common problems with condition monitoring systems are explicitly characterised to bring the models closer to the real-world case. False negatives and false positives (false ±), as discussed in section 2.2.4 are both taken account of.

False negatives are situations where the CM system does not detect a change in state of a damaged or deteriorating component, meaning the component will fail and a reactive repair or replacement is required. This is modelled by introducing a failure capture probability of the CM system, which is varied between 1.0 (no false negatives – i.e. base case assumptions) and 0.0 (100% false negatives – equivalent to reactive maintenance).

The technical impact of varying the failure capture probability is shown in Figure 72. This illustrates how the frequency of CBM actions decreases from around 1.4 actions to 0 actions as the failure capture probability reduces from 100% to 0%. During this same sequence the annual failure rate of the system increases from just over 0.7 to around 1.3 – this final failure rate is the equivalent of a purely reactive maintenance policy.

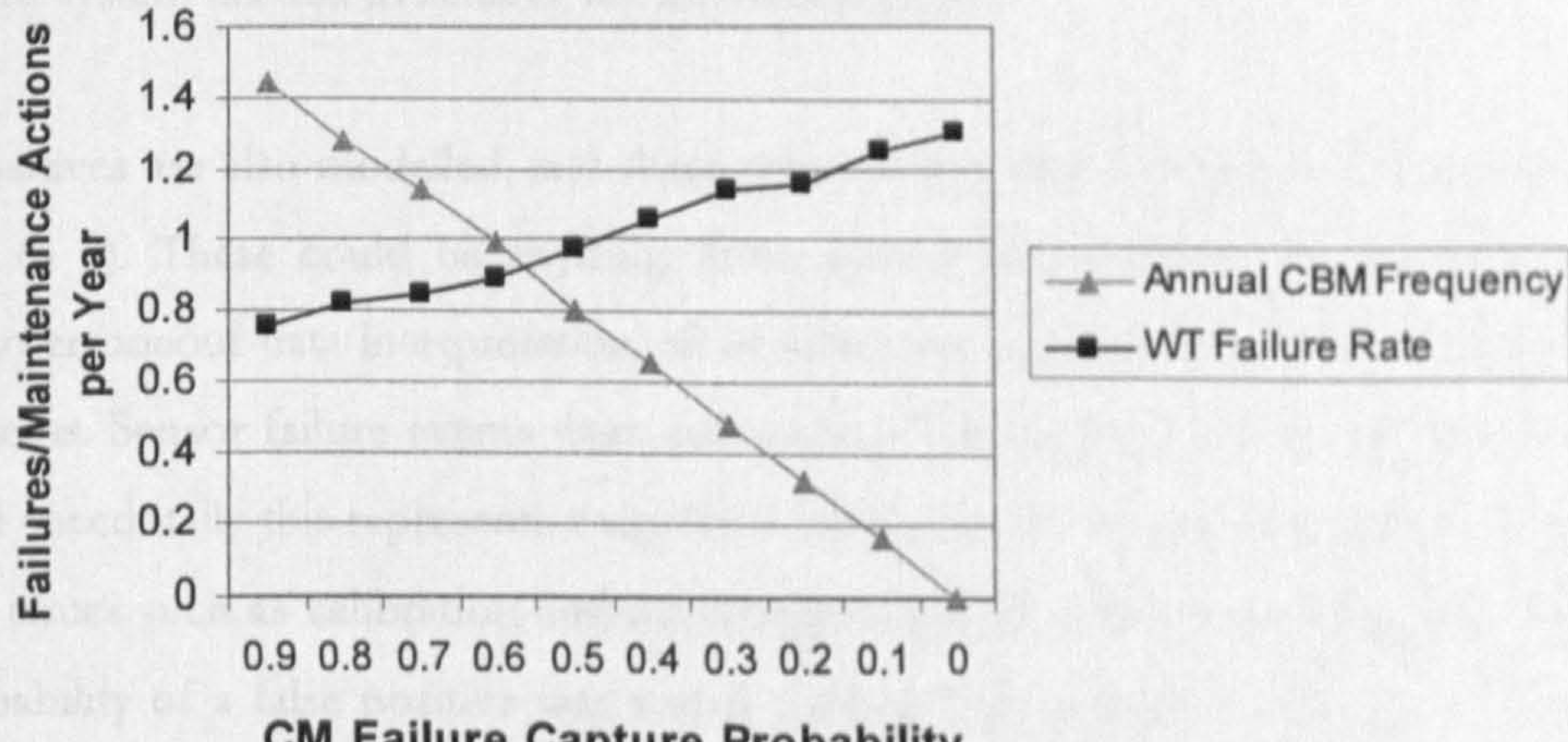

Figure 72: Technical Impact of CM Failure Capture Capability (False Negatives)

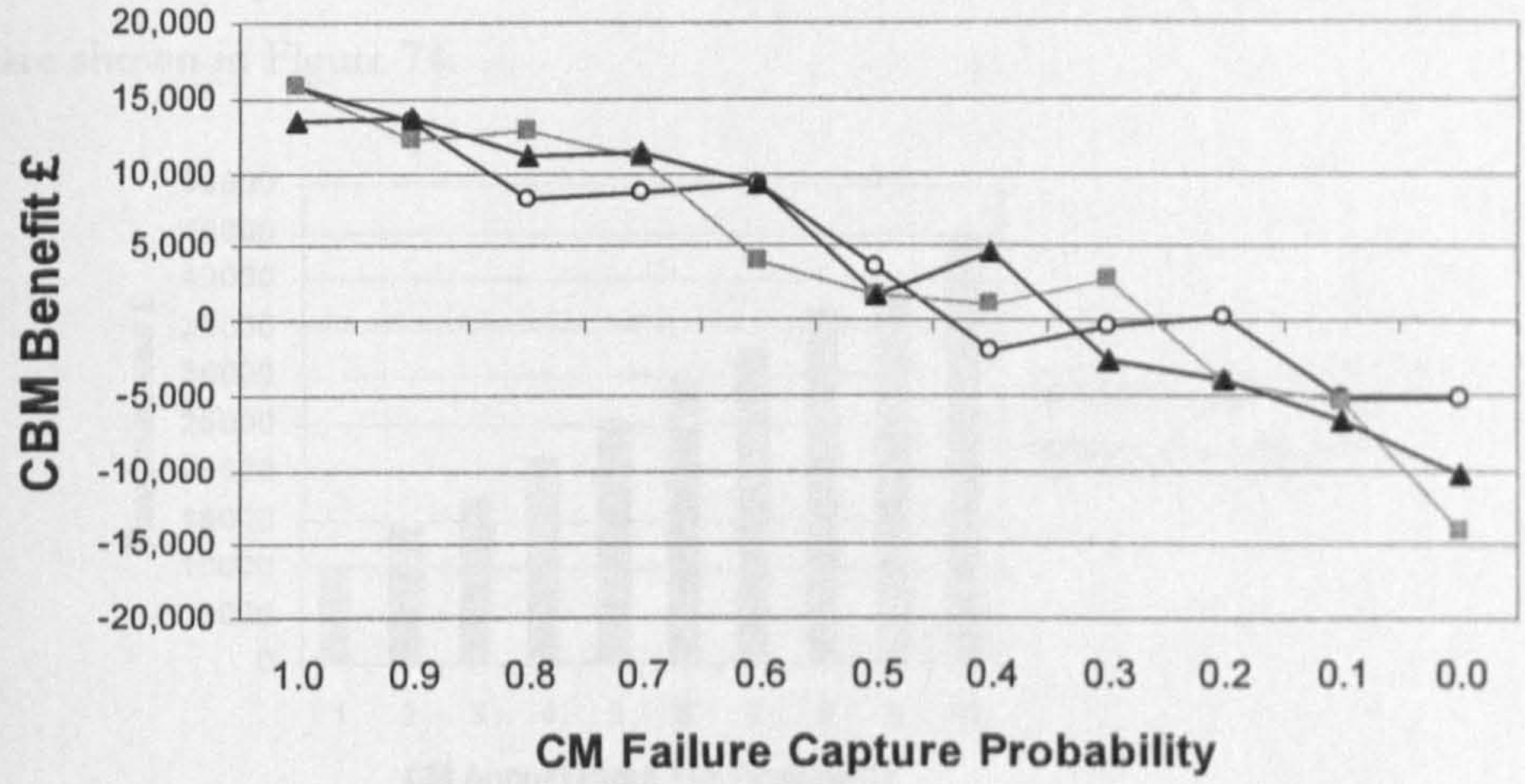

Figure 73: Revenue Impact of CM False Negatives

The impact of false negatives on CBM economic benefit is shown in Figure 73, for base case conditions and medium reliability levels (see section 5.1.4). Several simulations are plotted to give an indicaion of the uncertainty associated with the result. This illustrates that failure capture probability of around 50% or over is required to guarantee an economically justified WT CM system. In the range 50-30% failure capture probability, it is uncertain which policy is the more cost-effective. Below the threshold of ~30% accuracy, a TBM policy is more cost-effective than CBM. This is a useful result and is of particularly high relevance to wind farm operators wishing to appraise the relationship between the technical capabilities of CM and the economic benefits. It demonstrates the importance of the robustness and accuracy of the CM system needed to achieve the theoretical gains.

False positives are also modelled, and these occur at any time the system is functioning (i.e. states 1 to 8). These could be anything from sensor calibration issues, to sensor failure events, to erroneous data interpretation, all of which are significant problems in existing WT CM systems. Sensor failure events were estimated in Tavner et al. (2006) as 0.1 per annum, however anecdotally this represents a significant under-estimation of these events as a whole, because issues such as calibration and misinterpretation of data are not included. Therefore the probability of a false positive was varied starting from a base of 1 up to 10 events per annum – this range was speculative since no data on WT CM false positives could be found in literature. The impact of these events on revenue due to lost energy and spurious CBM actions are shown in Figure 74.

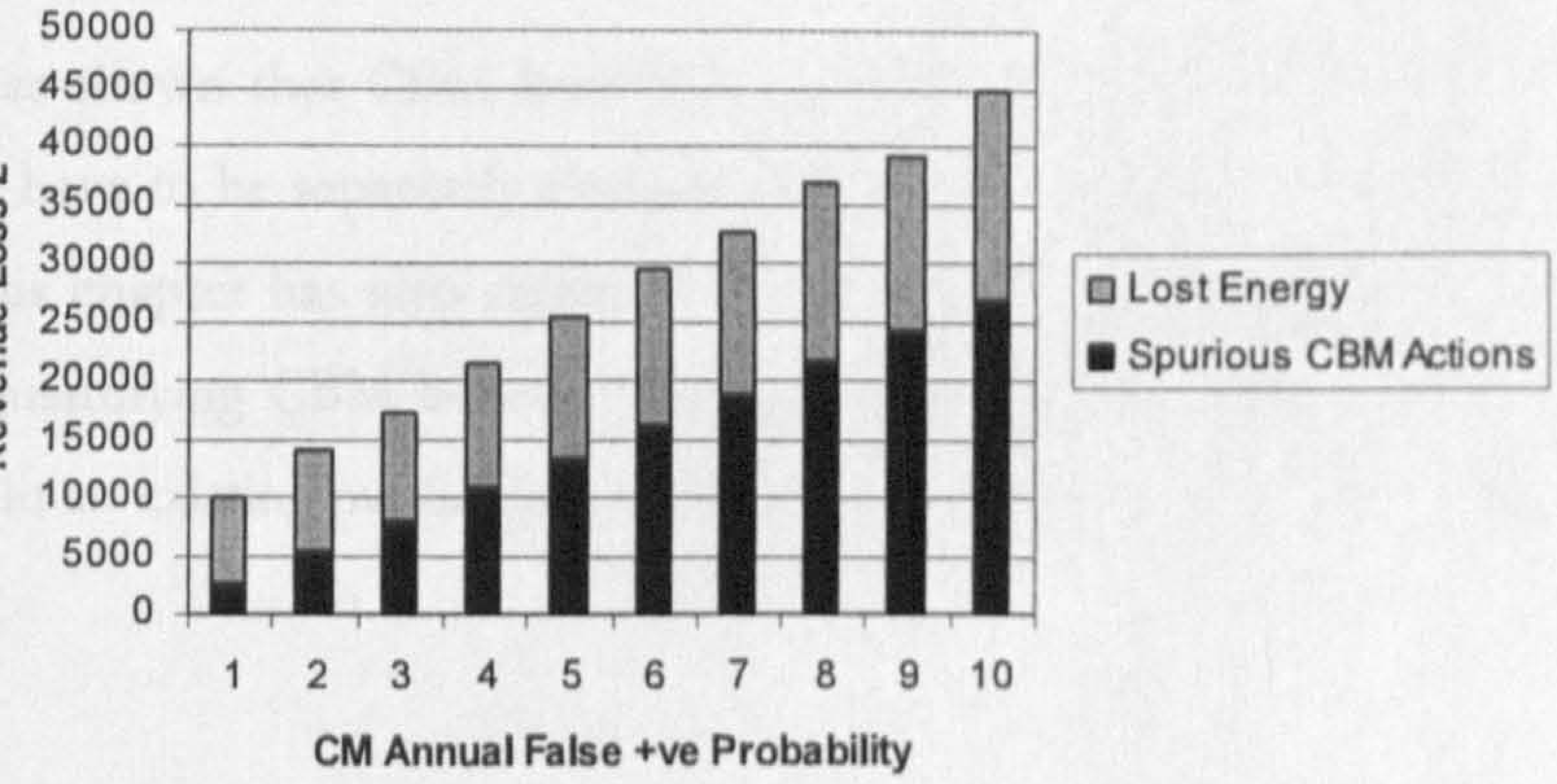

Figure 74: Economic Impact of CM False Positives

The lost energy component grows from £8,200 to £17,804 from annual occurrence of 1 to 10 respectively. This is significant, however the costs incurred by un-necessary mobilisation of labour and equipment become greater, although starting from a lower base.

The impact of false positives on CBM benefit is illustrated in Figure 75. This shows how the CBM benefit is eroded as the number of false positives increases. Figure 75 suggests that somewhere between 3 and 4 false positives per annum renders CBM less cost-effective than TBM for the conditions evaluated (med reliability, no false negatives). This is a significant result, since the cost penalties for more remote or offshore wind farms may be even more severe than those evaluated in this example.

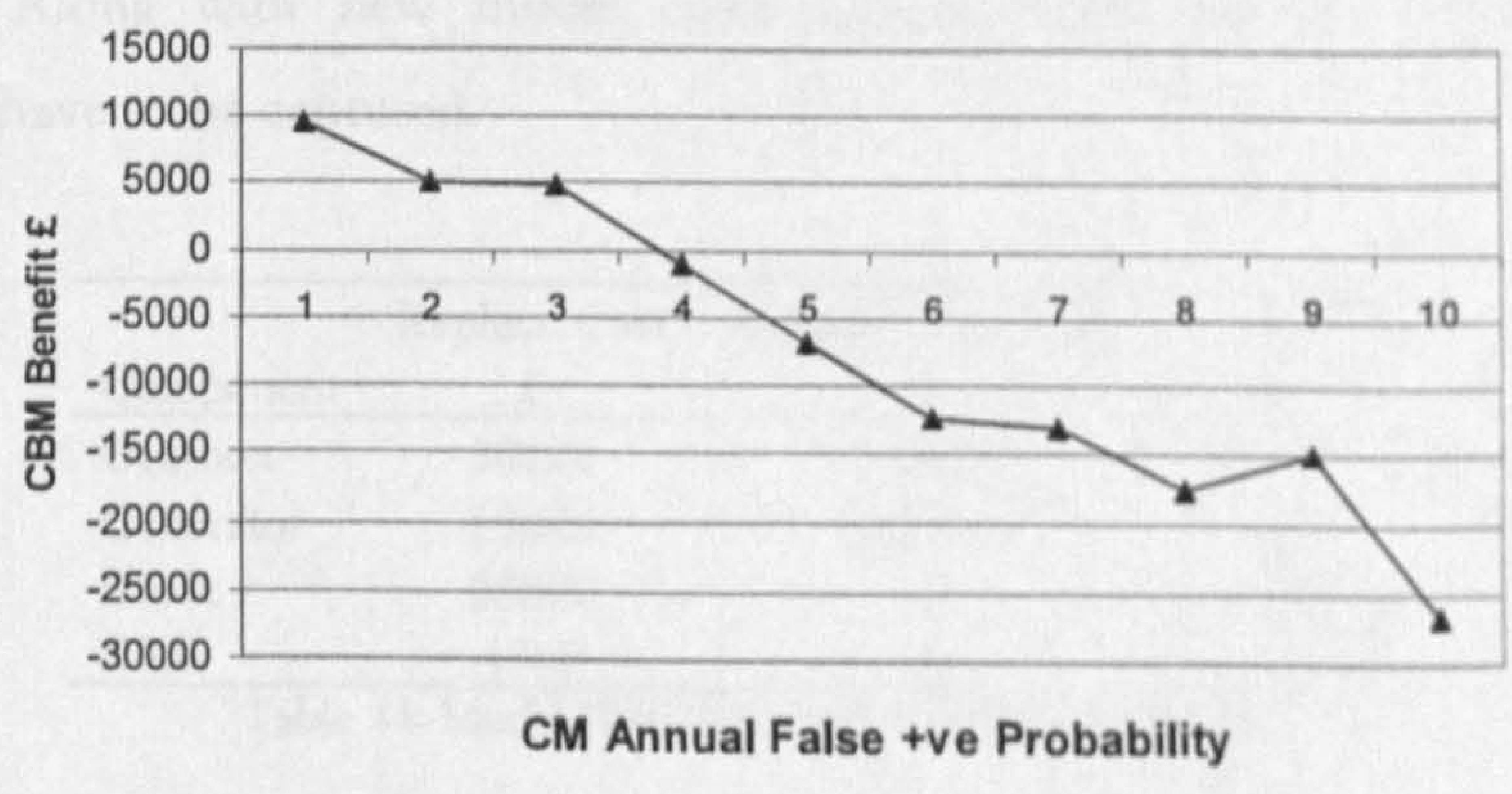

Figure 75: Impact of CM False Positives on CBM Benefit

These conclusions can be drawn for the specific circumstances evaluated in this example i.e. mean wind speed = 6.95 m/s, medium levels of reliability, base case maintenance costs etc.

This chapter has shown that CBM benefit is sensitive to several operating conditions and these would all have to be separately evaluated (these issues are discussed further in chapter 7). However this chapter has also shown that the models are capable of taking the factors involved and quantifying CBM benefit. The final step is to re-produce results which have been observed in an existing publication to provide another layer of model validation.

5.1.10 Comparison of Results with Existing Research

Research by academics at Robert Gordon University (Andrawus et al. 2006) into optimal wind farm maintenance policy has been conducted in the same period as the research contained in this thesis. The metrics and input assumptions used in the work of these researchers can be used as another demonstration of how the models presented in this thesis can be tailored for the available data.

The wind farm considered by Andrawus et al. (2006) is comprised 600kW units. The component costs, failure rates and downtime were provided in the paper and are re-created in Table 44. Along with new model costs and probabilities, the turbine curve and characteristics have to be captured.

Component	Replace Cost £	Annual Failure Rate λ	Downtime Days
Gearbox	50000	0.01282	120
Generator	19000	0.00641	60
Blade	28000	0	180
E&E	1500	0	0

Table 44: Model Details from Andrwus et al. (2006)

Manufacturers data for 600kW wind turbine units was sourced from a 'Wind Turbines and Wind Farms Database' (2008) and is shown in Table 45. This reference provided rotor radius (r) which is important when fitting the theoretical yield equation 33, which is re-stated below.

WT Rating MW	Rotor Radius M	Cut in, Cut out Wind Speed m/s	Capacity Factor % @ mean wind speed 6.95m/s
0.6	22	2.5, 24	36

Table 45: 600kW WT Characteristics

$$E_k = \frac{1}{2}\rho \, \pi \, r^2 v^3 (\times C_p)$$

The power curve for the 600kW wind turbine itself was provided in Wizelius (2006). Figure 76 shows the data points which were sampled and used to fit C_p in equation 33 (see 3.3.2).

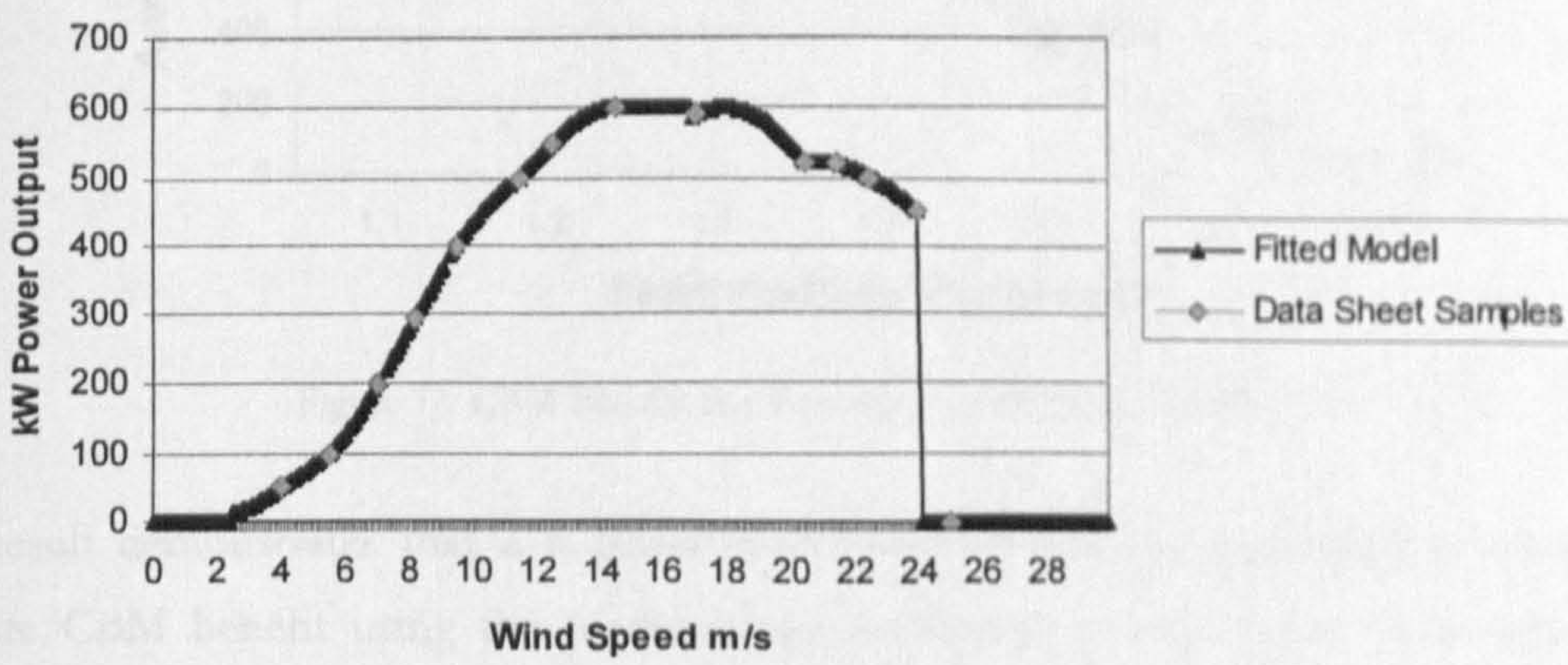

Figure 76: 600kW Power Curve

Other assumptions taken from the analysis of Andrawus et al. (2006) are that the cost of 6 monthly TBM is £5,304 and the incurred cost of CBM per annum excluding repairs is £3,390. Additionally, a catastrophic component failure incurs a component replacement cost rather than a repair cost. Furthermore, a subjective rating of the fault detection capability of the CM system was given as 3/5 which is implemented as 40% false negatives. Similarly, the reliability of CBM was given as 3/5.

The reliability of CBM is linked with the CM system itself, which in turn is dependent of the number of false positives the system produces. The CBM benefit for 1.1-1.7 false positives per annum are shown in Figure 77. The annual CBM benefit ranges from £1626 to £47. In their paper, Andrawus et al. (2006) calculate a CBM benefit of £385 per WT per annum. A similar figure is yielded if a CM false positive frequency of 1.5 per annum is adopted (see Figure 77). In this case the CBM benefit is £379, similar in magnitude to the values derived by Andrawus et al.

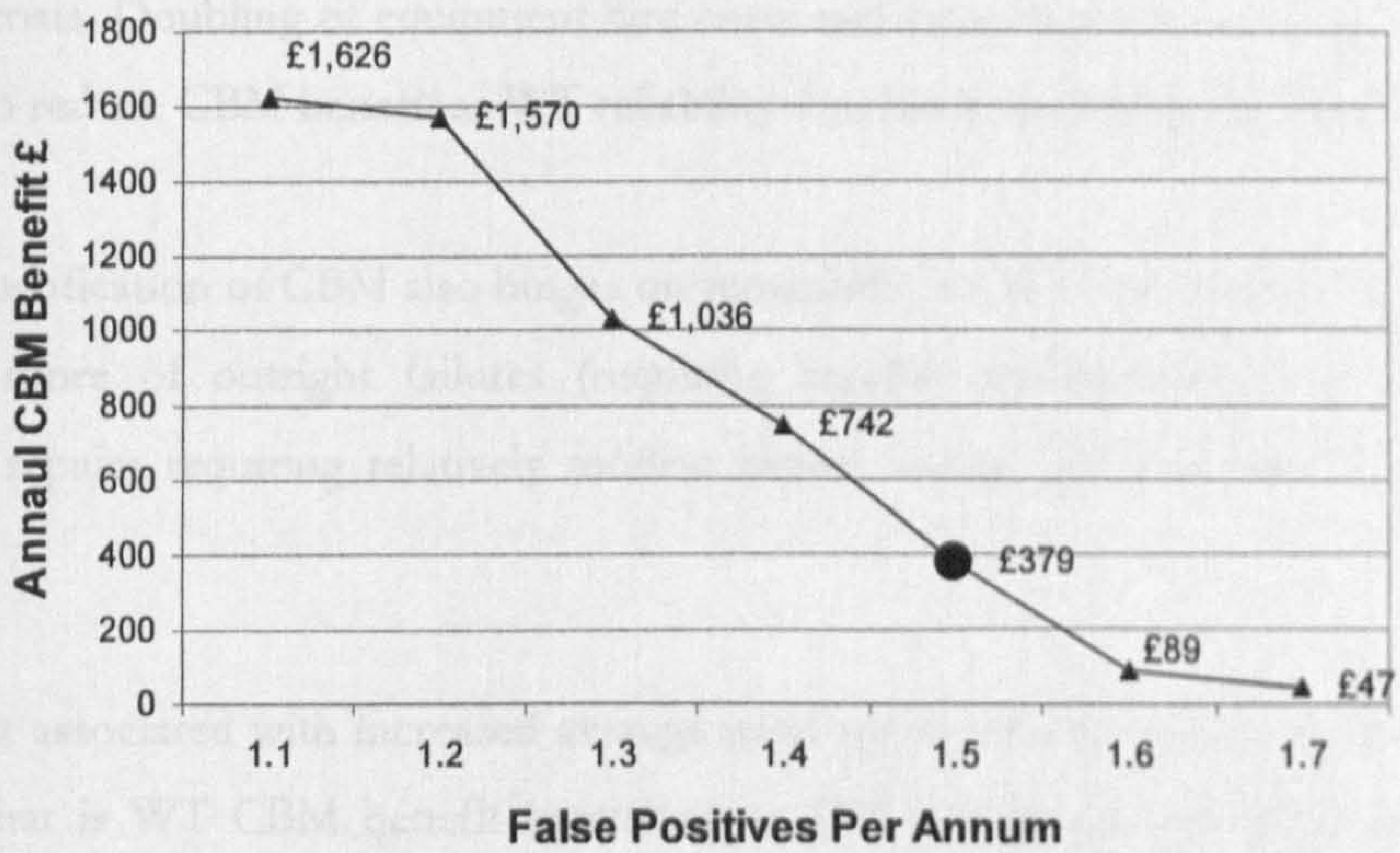

Figure 77: CBM Benefit as a Function of CM False Positives

This result demonstrates that it is possible to re-create specific conditions of interest to evaluate CBM benefit using the methodology developed in this thesis, even with fairly limited information on CM system performance and a small number of incidences of failure from a single wind farm. Such an example demonstrates the flexibility and applicability of the approach, for example a huge volume of time-stamped data is not required as with many other methods.

It could be argued that lack of consideration of temporal effects of long term deterioration (e.g. decades) is a simplification of the real case, however very few operational wind farms are at this stage of life and furthermore, the data are almost impossible to obtain. Therefore the approach proposed in this thesis represents a good compromise between input parameters and the value of its outputs.

5.2 Chapter 5 Summary

In this chapter, the results of investigation of the onshore WT model were investigated. The results showed that increased WT component costs significantly strengthen the case for onshore CBM (economic benefit approximately doubles). For onshore sites with modest wind resource (mean~6.95m/s), a high level of component reliability (i.e. $\lambda < 1$) enables CBM because of the resultant decreased maintenance frequency. Onshore CBM benefit is also highly dependant on cost of individual WT maintenance actions – labour and equipment costs. Doubling of equipment hire costs and increasing labour rates by 50% (C_{EQ} ,C_{LAB}) acts to reduce CBM benefit as WT reliability decreases (reversing the base case trend).

Economic justification of CBM also hinges on reparability of WT components after failure – if 90% or more of outright failures (requiring reactive maintenance) are fairly minor component repairs requiring relatively modest capital outlay, TBM is more cost-effective than CBM.

CBM benefit associated with increased average wind speed exhibits similar behaviour to the base case: that is WT CBM benefit increasing as WT component reliability decreases. If downtime for WT component failures is reduced, CBM benefit also reduces for the case of high and medium WT reliability. However, at a low level of WT reliability, the CBM benefit increases. This surprising result is discussed further in chapter 7.

Finally, WT CM system technical capability was appraised. The WT CM system has to detect 30-40% (or more) of all incipient WT component failures to be economically justified onshore (i.e. detecting the change from the Markov chain from 'fully up' state to a 'derated' state). Alternatively, the system can withstand up to 3 CM-induced false positives per annum and still be more cost-effective than TBM.

This chapter has dealt solely with quantifying CBM benefit under onshore conditions. The next chapter of this thesis focuses on offshore WTs, with the objective of answering one of the research questions proposed at the beginning of this thesis: 'Do offshore conditions enable economic viability of wind turbine CM systems?'

5.3 Chapter 5 References

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6 Application of Methodology and Models – Offshore Wind Turbine Model

The scenarios which have been presented so far have all been for onshore wind farms. One of the key assumptions regarding WT CM has often been that offshore conditions will enable more widespread use of the technology and subsequent implementation of CBM.

There are a number of significant differences between offshore wind farms as compared to their onshore equivalents. Turbine ratings are likely to be much larger as a result of economies of scale – it does not make financial sense to build small offshore wind farms due to the large infrastructure costs associated with foundations and grid connection. Furthermore, wind profiles are generally very strong offshore due to small surface friction and a lack of obstacles. The combination of larger WT ratings and stronger wind profile offshore means that higher volumes of energy capture per turbine are expected than a typical onshore WT. These large-rated offshore WTs have higher capital costs, component costs, and repair costs. Additionally the specialised crane vessels required to perform maintenance actions are much more expensive than the onshore equivalents, although the magnitude of the increase is the subject of debate due to a current lack of experience in offshore projects.

It is generally accepted that unplanned downtime will increase, mainly because of offshore logistics difficulties (floating platform/ jack up crane vessel lead times which have been quantified at around 10 days (Phillips et al., 2005)), more severe access constraints because of adverse weather, and sub-component supply chain bottlenecks due to less mass-production of offshore WTs.

In terms of electricity generated, it is expected that future offshore wind farms in the UK will be subject to increased revenues as they will gain more than 1 ROC per MWh generated. At the time of writing it was suggested that offshore projects would gain 1.5 ROCS per MWh (BERR, 2007).

All of these aspects must be captured within the models developed in this research for an adequate analysis of the techno-economic benefits of CM for offshore wind farms. Therefore the onshore models used up until now were modified – these changes are detailed in the next section.

6.1 Offshore Wind Turbine Model

The parameters of the onshore model were adjusted taking account of the issues discussed in section 6. Capital cost estimates of £1m per MW were assumed for offshore installations – 5MW capacity was assumed – and the resultant parameter values in Table 46 were adopted for the offshore model.

Metric	Gearbox	Generator	Rotor Blade (1)	E&E	ROCs per MWh
Replace Cost	£400,000	£200,000	£300,000	£20,000	# / £
Downtime	41 Days	32 Days	41 Days	2 Days	1.5/ 60
WT Rating	C_{LAB}	C_{EO}	Maintenance Freq.	Base Case Failure Rates	
5MW	£1,800	£15,000	12 months	Tavner et al. 2007	

Table 46: Offshore Model Parameter Summary

Information from a 5MW offshore WT data sheet was used (RePower, 2005) to construct Table 47 and to fit the power curve to the theoretical yield equations (see Figure 78). The same experimental steps that were carried out for the onshore wind analysis are repeated for these offshore conditions, to explore the techno-economic case for CBM in the offshore environment.

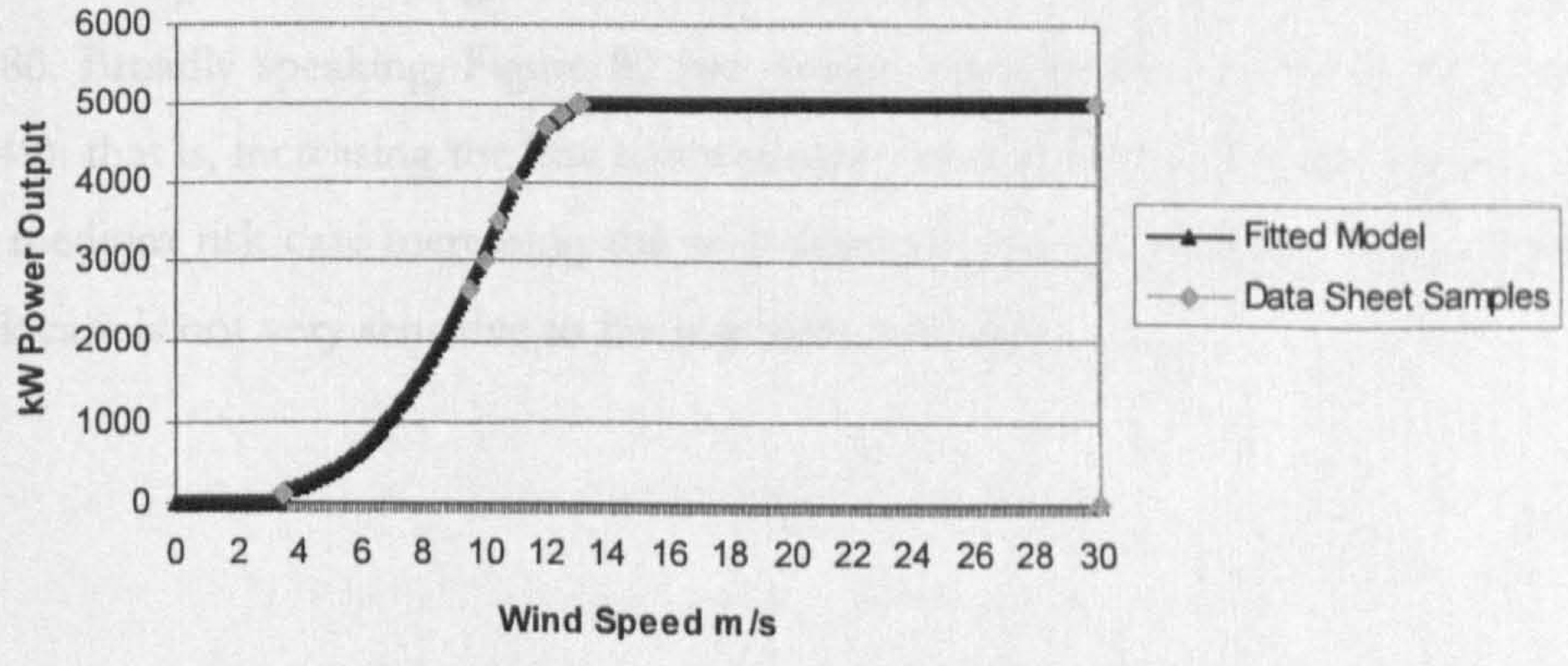

Figure 78: 5MW Offshore WT Power Curve

WT Rating	Rotor Radius	Cut in, Rated, Cut out Wind Speed	Capacity Factor
MW	M	m/s	% @ mean wind speed 6.95m/S
5	61.5	3.5, 13, 30	28.9

Table 47: 5MW Offshore WT Characteristics

Firstly, the offshore model was analysed in order to determine a suitable CBMDM wait time. Although the capital costs of a 5MW offshore wind turbine are much higher than the 2MW onshore equivalent, the component costs were still derived based on the proportions in Table 21. Since it is assumed that the probabilities of failure after occurrence of incipient fault do not alter (see Table 24), the magnitude of the risk levels for each state will increase in proportion with each other. This is shown in Figure 79, which shows low risk (risk<2000), medium risk (2000<risk<6000) and high risk (risk>6000) states in the same classification as the onshore model.

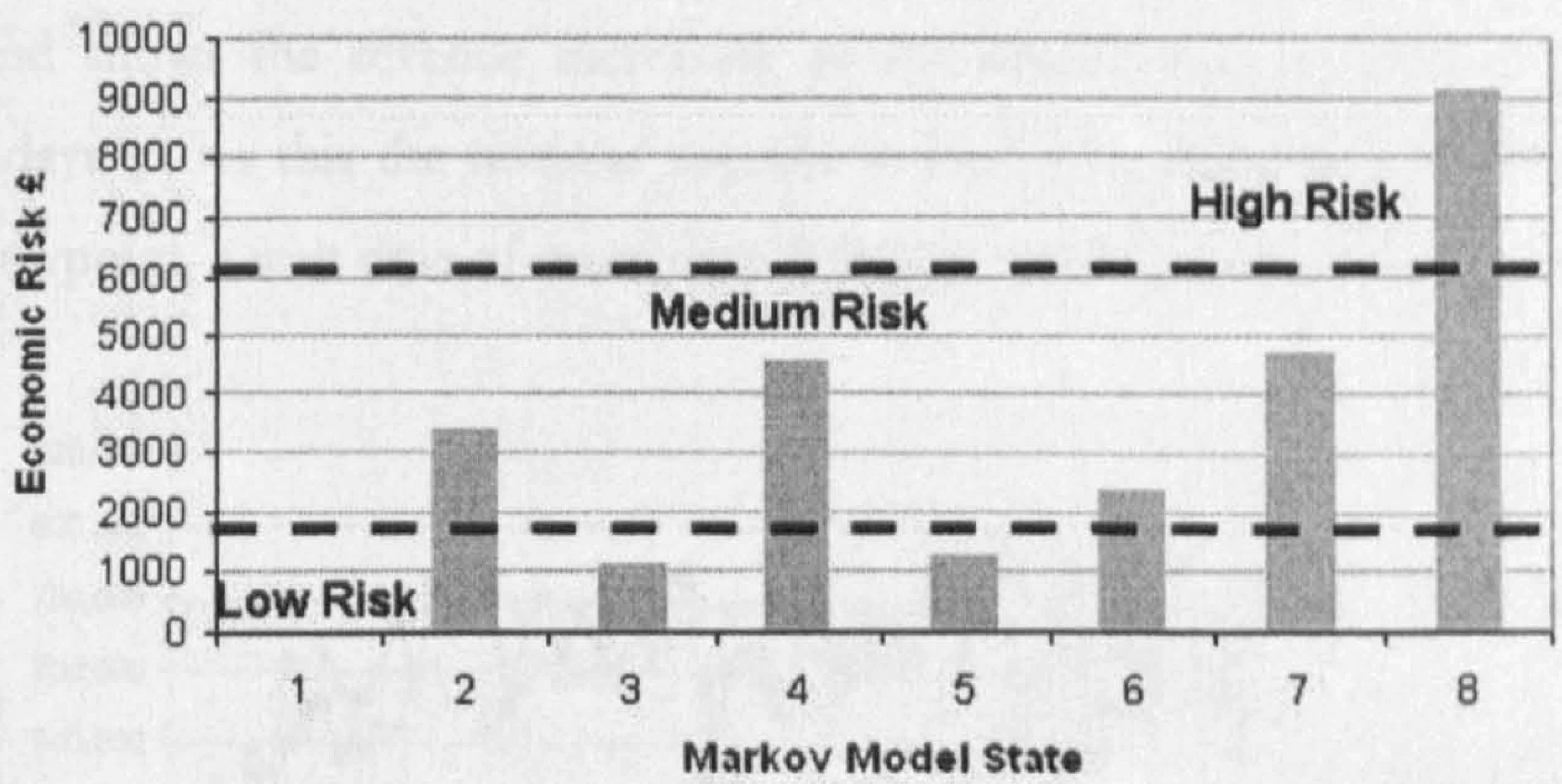

Figure 79: Offshore Risk Classification

The revenue impact of varying the CBMDM wait time for the three risk levels is shown in Figure 80. Broadly speaking, Figure 80 has similar characteristics to the onshore case (see Figure 49): that is, increasing the low risk wait time has a positive effect on revenue, whereas for the medium risk case increasing the wait time reduces the revenue. The revenue in the high risk case is not very sensitive to the wait time variation.

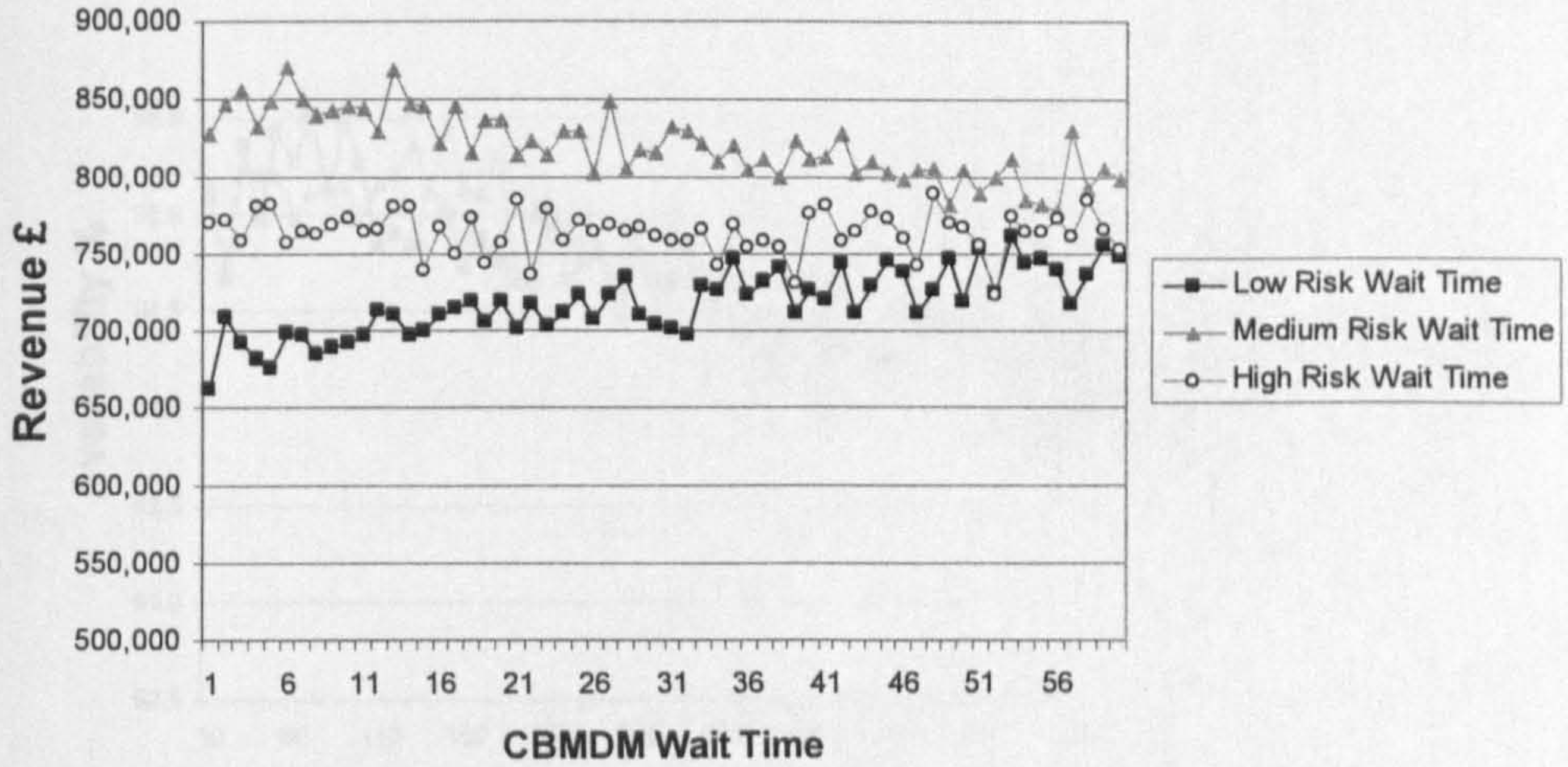

Figure 80: Revenue Impact of Risk-Based CBM Interval for All Risk Levels – Offshore

The low risk maintenance interval is examined over a greater range (10-600 days) in Figure 81. The trend shows the revenue increasing as the maintenance interval is increased to around 200 days. After this the revenue appears to level out, suggesting that from a purely economic viewpoint, a wait time of more than 200 days would be desirable.

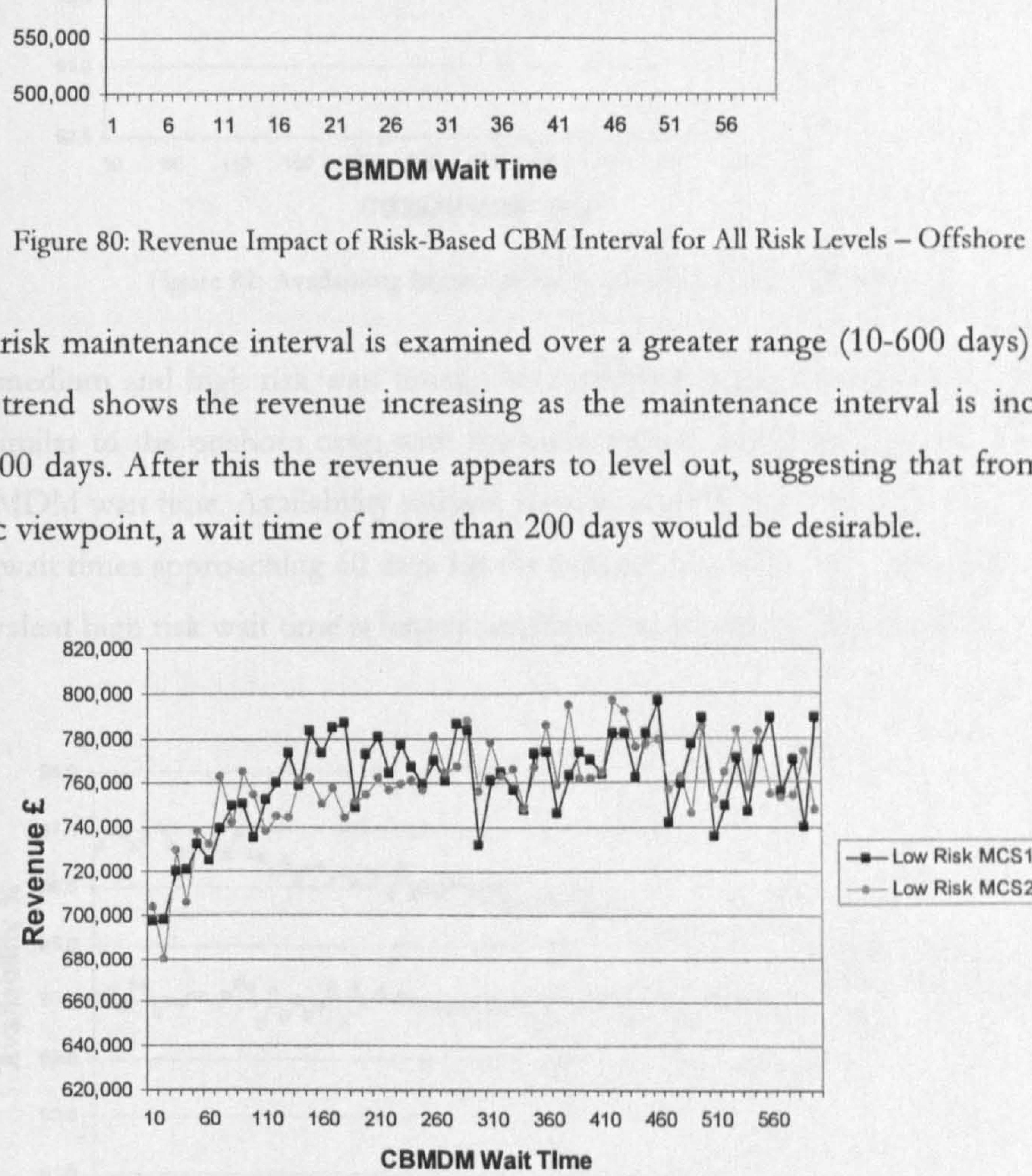

Figure 81: Revenue Impact of Low Risk Wait Time – Offshore

The negative impact on availability (technical impact) over the same range of wait times is shown in Figure 82. Availability peaks at around 50 days wait time. Since it is expected that offshore yields will be substantially higher than onshore, making availability more important, the wait time of 100 days for the onshore case is reduced to 50 days for the offshore model.

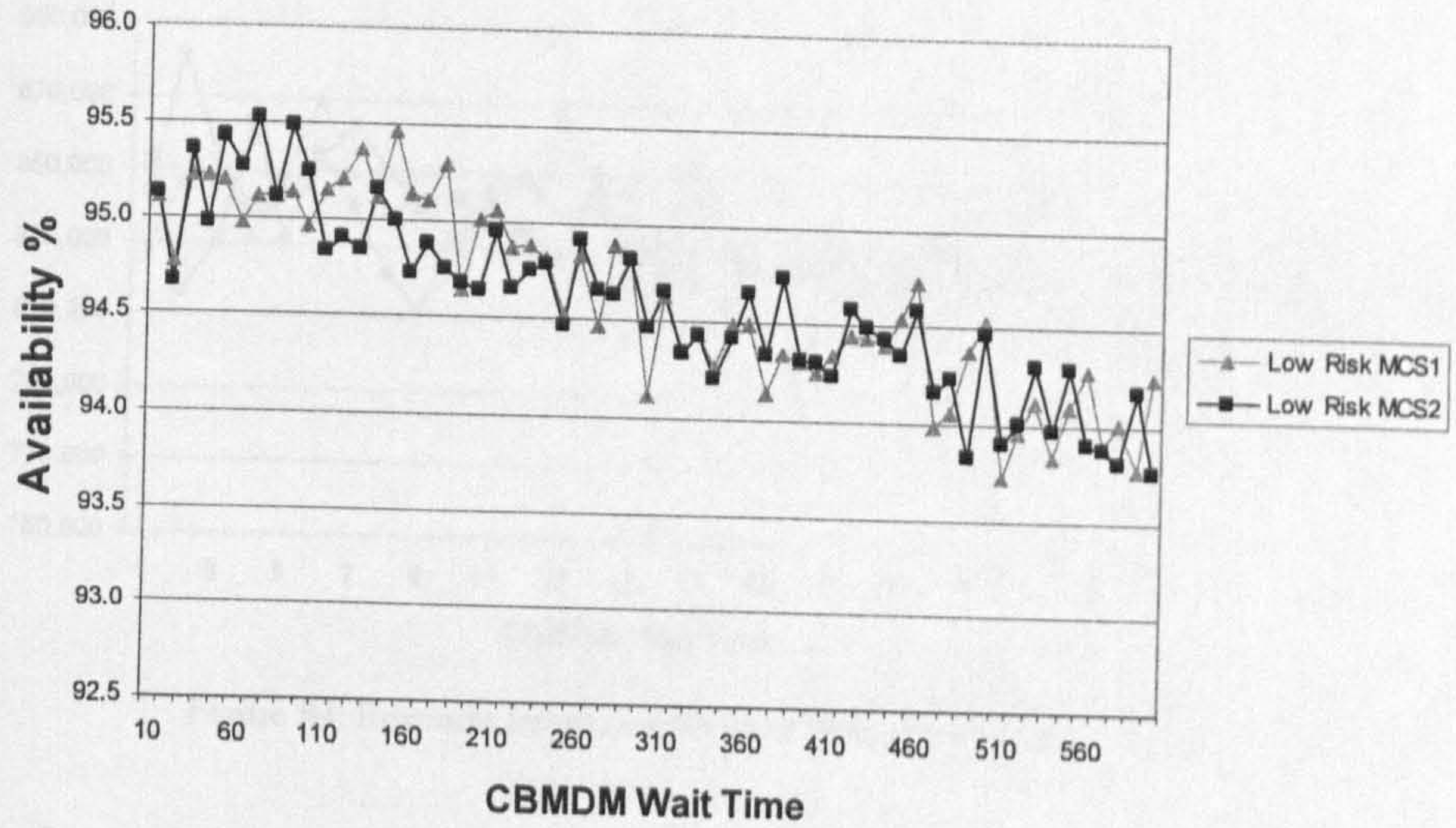

Figure 82: Availability Impact of Low Risk Wait Time - Offshore

For the medium and high risk wait times, the availability impact is illustrated in Figure 83. This is similar to the onshore case, with the medium risk availability being clearly coupled with CBMDM wait time. Availability reduces from around 97% for low wait times to around 95% for wait times approaching 60 days for the medium risk wait time. Over the same range, the equivalent high risk wait time is largely unaffected at around 94% availability.

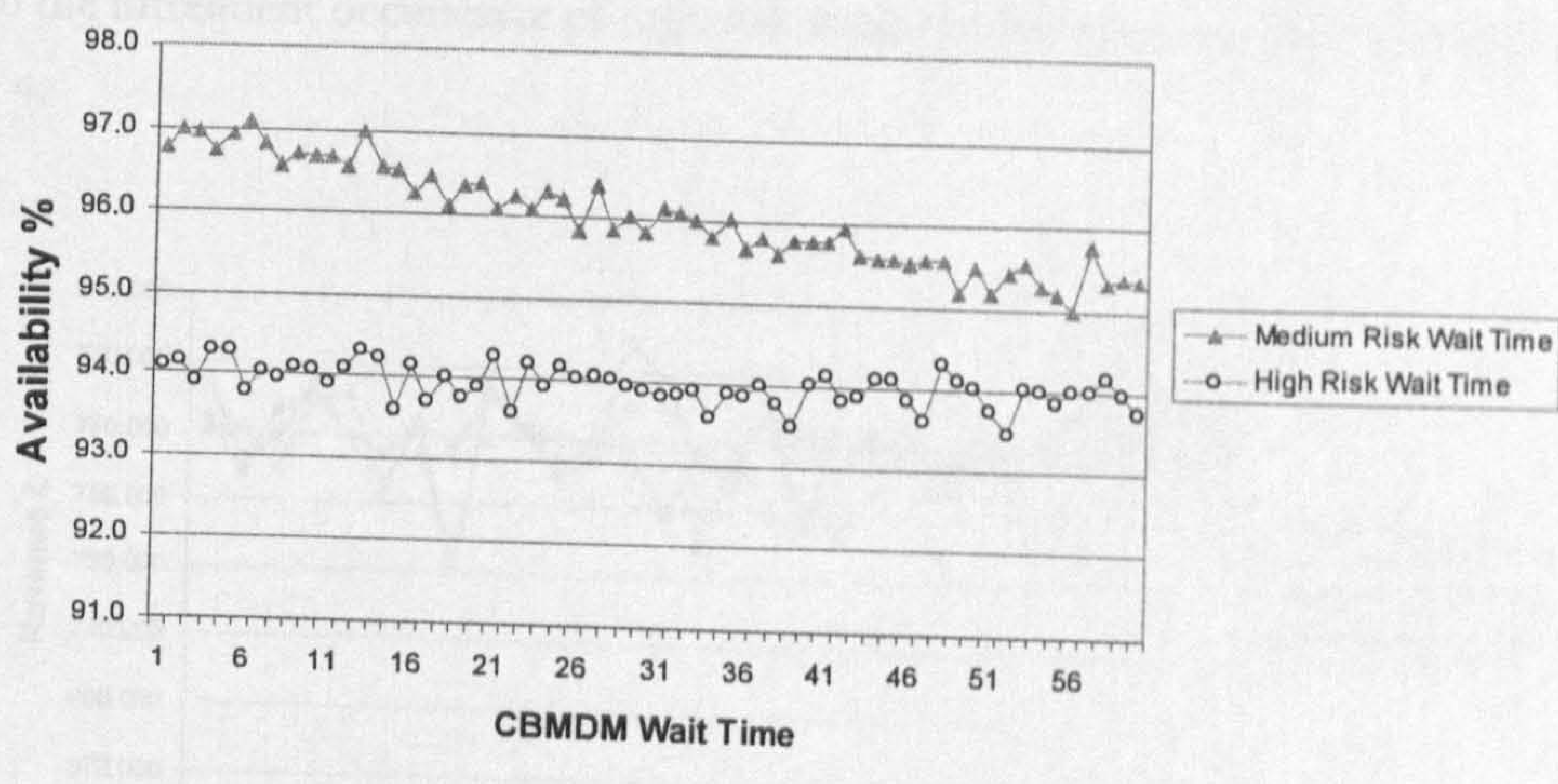

Figure 83: Availability Impact of Medium and High Risk Wait Time - Offshore

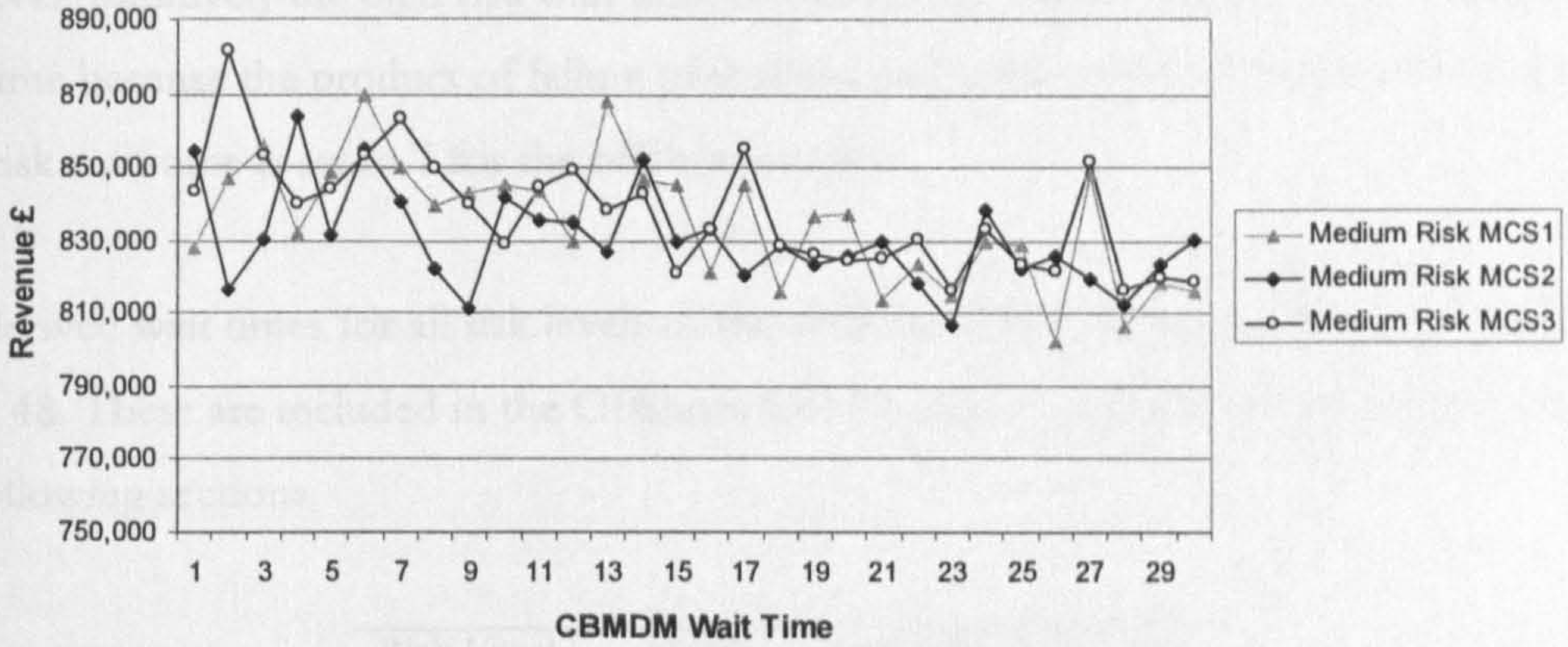

Figure 84: Revenue Impact of Medium Risk Wait Time - Offshore

Figure 84 shows the revenue impact of varying the medium risk wait time over the range 1-30 days. There is more variation in the offshore revenue values compared to the onshore case (see Figure 55). The revenue is highest for low wait times, and for this reason a CBMDM wait time value of 7 days is selected, as this maximises revenue and gives ample time to organise maintenance resources and crews.

Finally, Figure 85 shows the revenue impact of high risk wait time, over the range 1-30 days. The revenue is not sensitive to wait time variation compared with the other risk levels. This is due to the infrequent occurrence of high risk states, as discussed previously at the end of chapter 4.

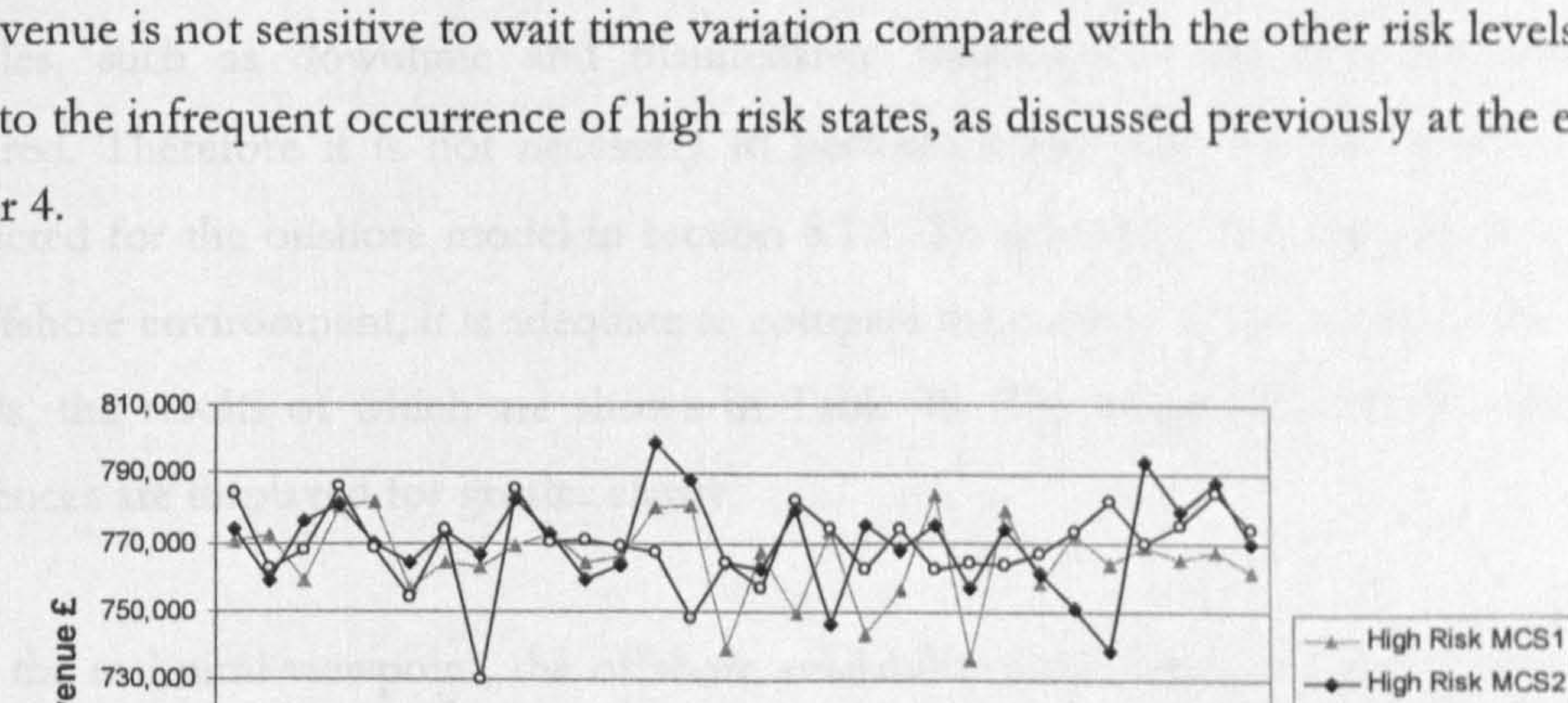

Figure 85: Revenue Impact of High Risk Wait Time – Offshore

However, intuitively the high risk wait time should be less than or equal to the medium risk wait time because the product of failure probability and impact (cost) is large. Therefore the high risk wait time is set to 7 for the offshore model.

The derived wait times for all risk levels of the offshore CBMDM model are summarised in Table 48. These are included in the Offshore CBM techno-economic analysis contained in the following sections.

Risk Level	States	CBMDM Wait Time Days
High Risk	8	50
Medium Risk	2, 4, 6, 7	7
Low Risk	3, 5	7

Table 48: Derived Risk-Based CBM Wait Times – Offshore Model

6.1.1 Model Validation and Onshore Wind Turbine Model Comparison

To enable the offshore analysis, the only changes to the models are the magnitude of input variables, such as downtime and maintenance frequency – the program structure is unaltered. Therefore it is not necessary to perform a thorough model validation as was conducted for the onshore model in section 5.1.1. To appreciate the changes as a result of the offshore environment, it is adequate to compare the outputs of the onshore and offshore models, the results of which are shown in Table 49. The magnitude and direction of the differences are displayed for greater clarity.

From the technical viewpoint, the offshore availability drops by 1.74% due to less frequent maintenance actions and longer downtimes. The offshore failure rates also increase because of the reduction of TBM frequency to 1 action per annum. These technical trends applied to offshore WTs have been anticipated by many commentators, industrialists and academics including van Bussell & Zaaijer (2001), Marsh (2007) and Giebhardt et al. (2007). Despite the lower availability and reliability, the offshore yield and revenue are much higher, which is because of the 5MW rating and higher number of ROCs per MWh generated – see Table 46.

The same wind profile (mean = 6.95m/s) and Markov TPM is used for both cases. The size of the WT rating is also the principal reason for the larger lost energy in the offshore case – £52,700 (549 x 96) – compared with the onshore case – £10,433 (137 x 76). Simply quantifying these onshore/ offshore differences is of value: however the primary goal is to observe the effect of offshore conditions on the technical and economic case for CM.

Annual Metric		Onshore TBM	Offshore TBM	Difference	Onshore ±L	Offshore ±L
Availability (%)		97.26	95.52	-1.74	0.2009	0.3132
Yield (MWh)		5,068	12,029	+6,961	13.1	43.5
Revenue (£/year)		308,807	827,420	+518,613	4,606 (1.9%)	23,432 (2.8%)
Maintenance Freq. (act/yr)		2.000	1.000	-1.00	NA	NA
Failure Rates	Overall Turbine	1.054	1.2642	+0.21	0.056009	0.058249
	Gearbox	0.092	0.1467	+0.05	0.018561	0.022697
	Generator	0.109	0.1633	+0.05	0.015206	0.020761
	Blade	0.218	0.3117	+0.09	0.018818	0.031174
	E&E	0.635	0.6425	+0.01	0.042429	0.043239
Lost Energy (MWh/year)		137.275	548.960	+411.68		

Table 49: Comparison of TBM for Onshore & Offshore Conditions

6.1.2 Offshore Wind Turbine Base Case Evaluation of Condition Monitoring Benefit

The results of the offshore base case comparison between TBM and CBM are shown in Table 50 and Figure 86. The results are broadly similar to the onshore case – the CBM policy increases the availability, yield and revenue, while decreasing the failure rates and lost energy.

Annual Metric		TBM	CBM
Availability (%)		95.52	97.76
Yield (MWh)		12,029	12343
Revenue (£/year)		827,420	841712
Maintenance Freq. (actions/year)		1.000	2.413
Failure Rates	Overall Turbine	1.2642	0.8775
	Gearbox	0.1467	0.0058
	Generator	0.1633	0.0692
	Rotor Blade	0.3117	0.1267
	E&E	0.6425	0.6758
Lost Energy (MWh/year)		548.960	235.77

Table 50: Offshore Base Case Evaluation of TBM & CBM

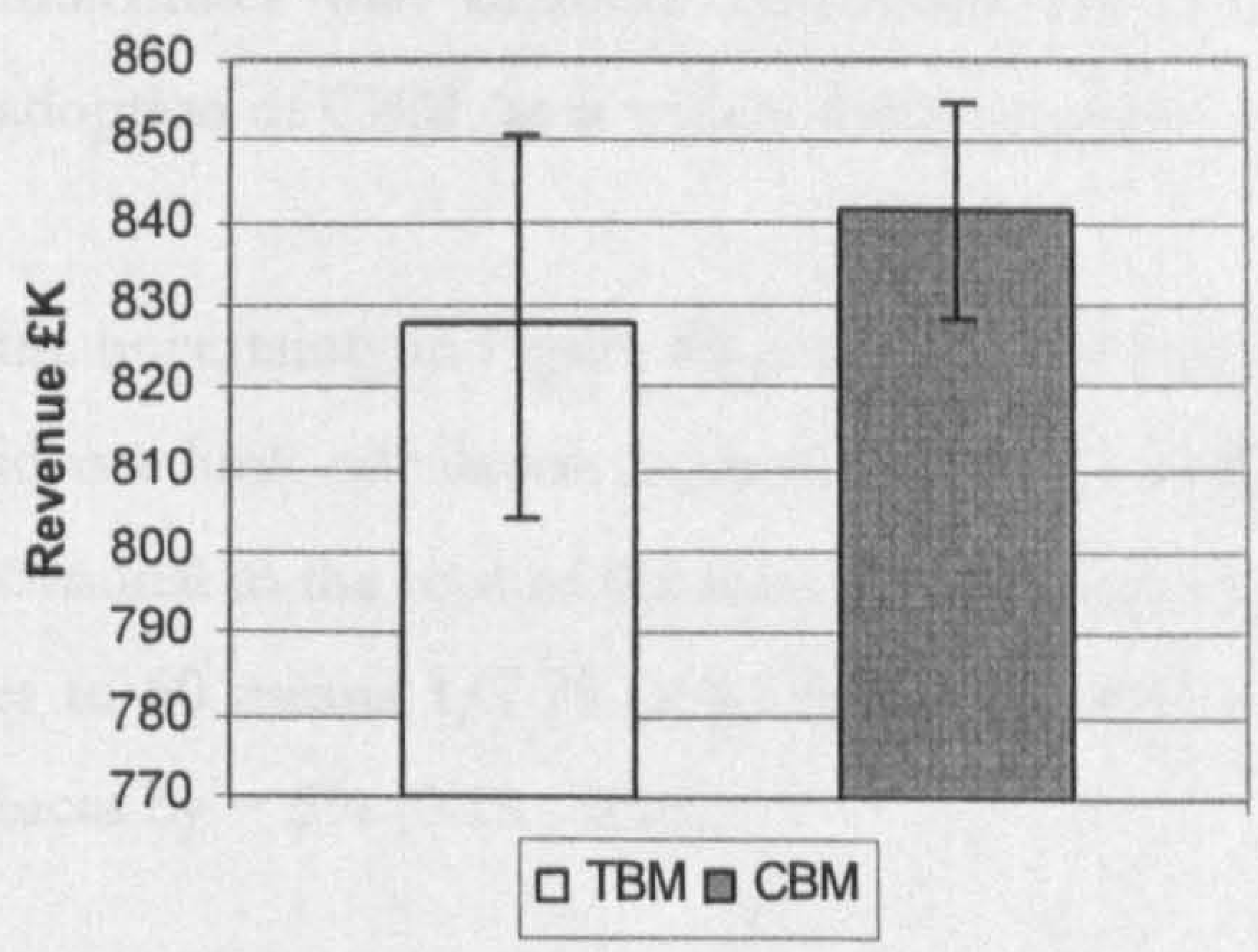

Figure 86: Offshore Base Case Revenue Comparison of TBM & CBM

The main difference is that adoption of a CBM maintenance policy increases the frequency of maintenance actions, contrasting with the onshore base case where the maintenance frequency was reduced on adoption of CBM. There are two reasons for this. One is that the offshore TBM frequency is only one action per annum, compared to two actions per annum onshore. Secondly, the shorter wait times derived for the offshore CBMDM model (high, medium, low risk wait times = 7, 7, 50 offshore compared to 15, 15, 100 onshore) mean that maintenance is carried out more frequently. It is noted that these maintenance actions are constrained by a wind speed access model in exactly the same way as the onshore model (i.e. according to Table 30). However, this model neglects wave height which is a significant obstacle to offshore operations (e.g. heavy lifting of nacelle components). This means that the access model presented in these results will paint a more optimistic picture of offshore WT maintenance than encountered in real operations.

Returning to the results in Figure 86, the net benefit of CBM is calculated as £14,293 per wind turbine per annum. Although the CBM economic benefit is larger than that obtained for onshore conditions (£7,288 – in section 5.1.2), the magnitude of the confidence limits in Figure 86 is an issue worth investigating. As a percentage of the total revenue, L for offshore results (2.8% - see Table 49) is similar to onshore (1.9%). However because of the greater magnitude of the variance (number of samples and t-score stay constant - see equation 39 in chapter 4) the confidence limits for offshore are almost an order of magnitude larger than onshore (±£23,432 offshore c.f. ±£4,606 onshore). Nevertheless, Figure 86 is an interesting result, because it demonstrates that offshore conditions are not automatically a clear economic enabler for adoption of CBM (as is widely thought), given the confidence limits.

One way of reducing the uncertainty in Figure 86 is to run more MCS. However because of the nature of the confidence limit calculation (equation 39), the confidence limit reduces in a manner inversely proportional to the root of the number of samples (N). Therefore doubling the number of samples to 60 means 1/7.75 (x 0.13) as opposed to 1/5.48 (x 0.18) for 30 samples, i.e. L only reduces by ~ 5% (0.18 - 0.13).

Therefore caution must be used when interpreting the offshore results re: magnitude of the confidence limits relative to CBM benefit.

6.1.4 Offshore Wind Turbine Base Case Sensitivity to Component Reliability Levels

The three reliability levels defined in Figure 62 were input to the offshore models to establish if coupling exists between reliability and offshore CM benefit. Figure 88 shows that the CBM benefit is highest if the WT units are relatively reliable (£69,993), and the benefit of CBM relative to TBM decreases as the WT units become less reliable (med reliability CBM benefit = £66,595). Even for the low reliability case, CBM is significantly more cost-effective than TBM (low reliability, CBM benefit = 28,012).

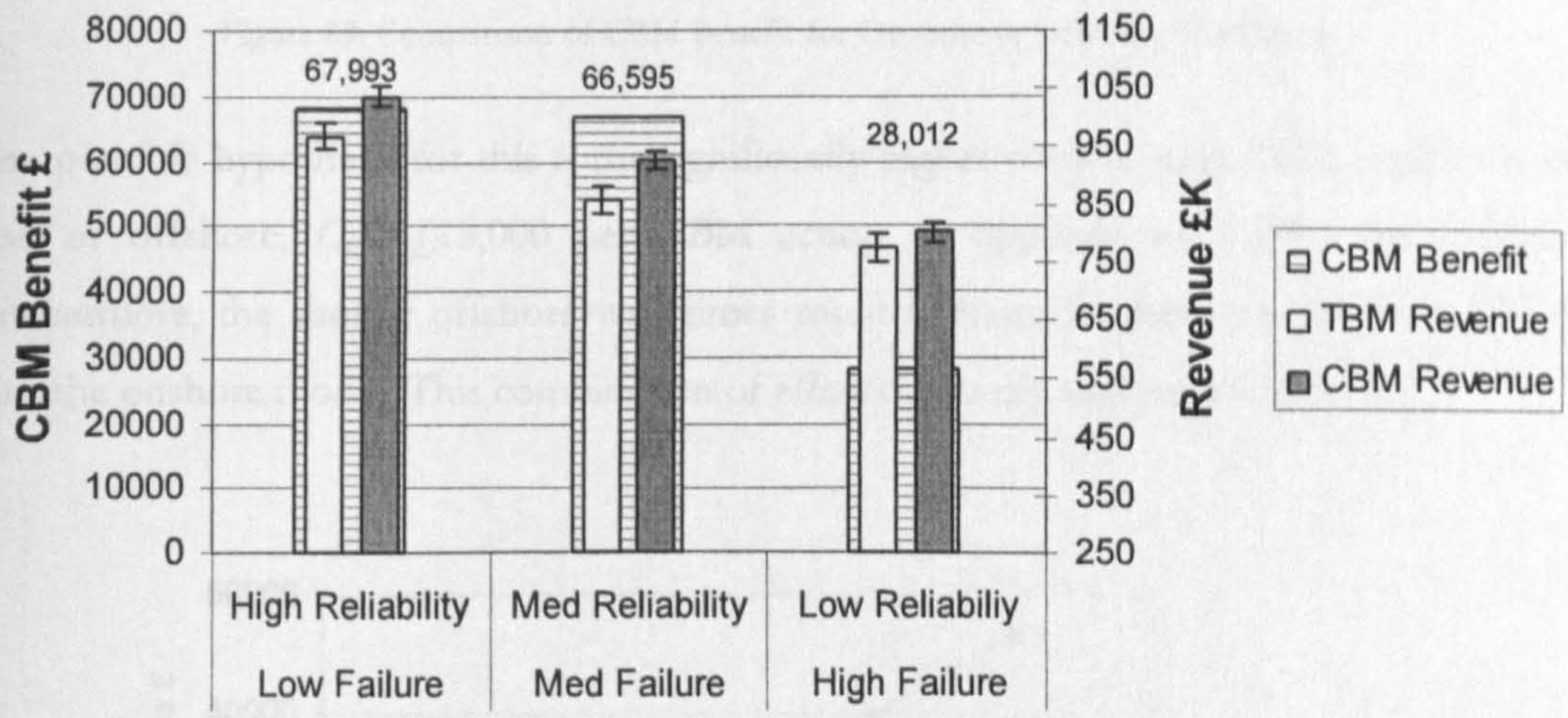

Figure 88: Impact of Reliability Level on Offshore TBM & CBM Revenue

There appears to be coupling between reliability and CBM benefit in the offshore case, and it is interesting to note that the trend is the opposite of the onshore case, where CBM benefit increased with reducing reliability (see Figure 63, chapter 5). Figure 89 shows a direct comparison between the CBM benefit for the offshore and onshore sensitivity to WT reliability level.

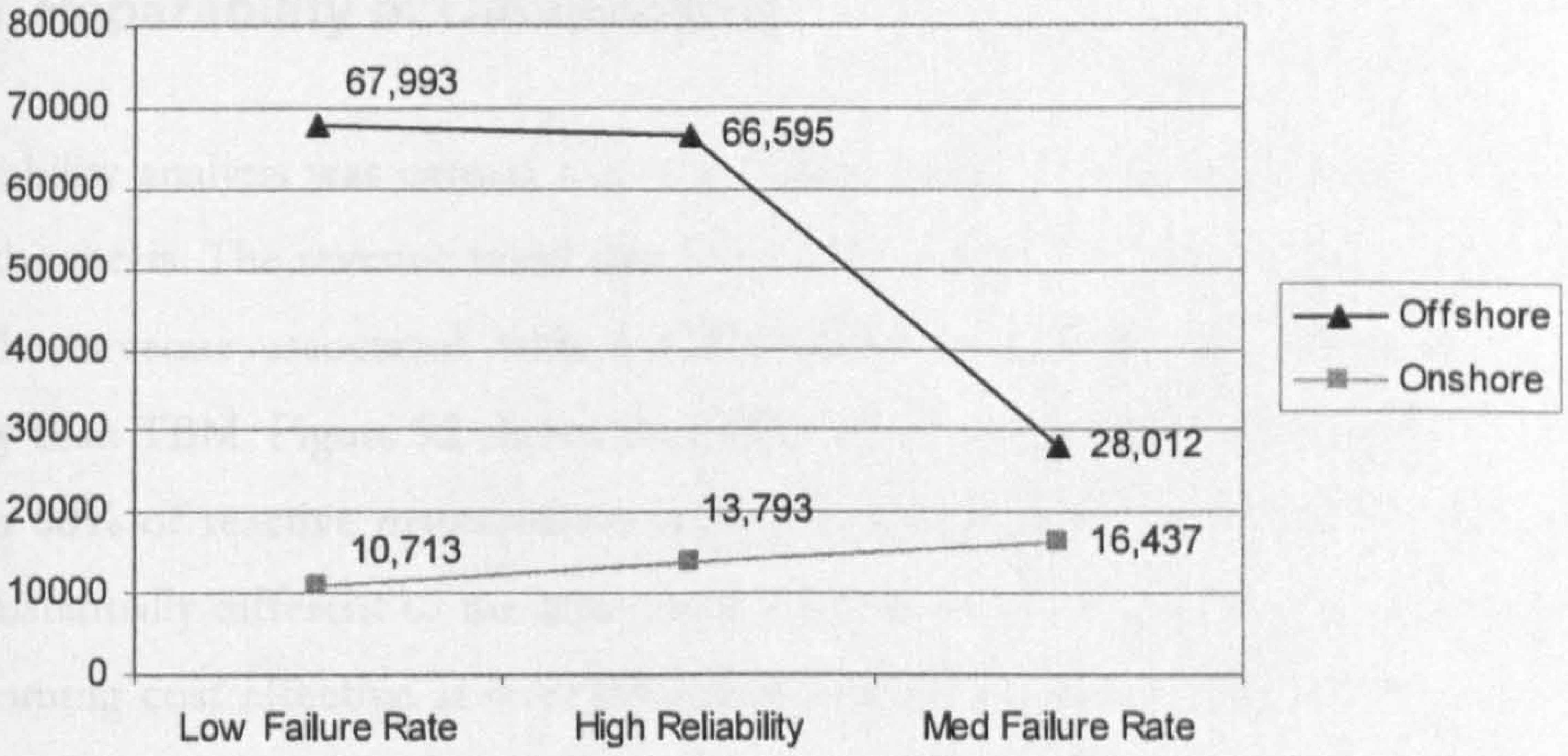

Figure 89: Comparison of CBM Benefit for Onshore & Offshore Conditions

One possible hypothesis for this is the significantly higher costs of each CBM action. In the case of offshore, C_{EQ}=£15,000 per CBM action as opposed to £1,500 for onshore. Furthermore, the shorter offshore wait times result in more frequent maintenance actions than the onshore model. This combination of effects is clearly shown in Figure 90.

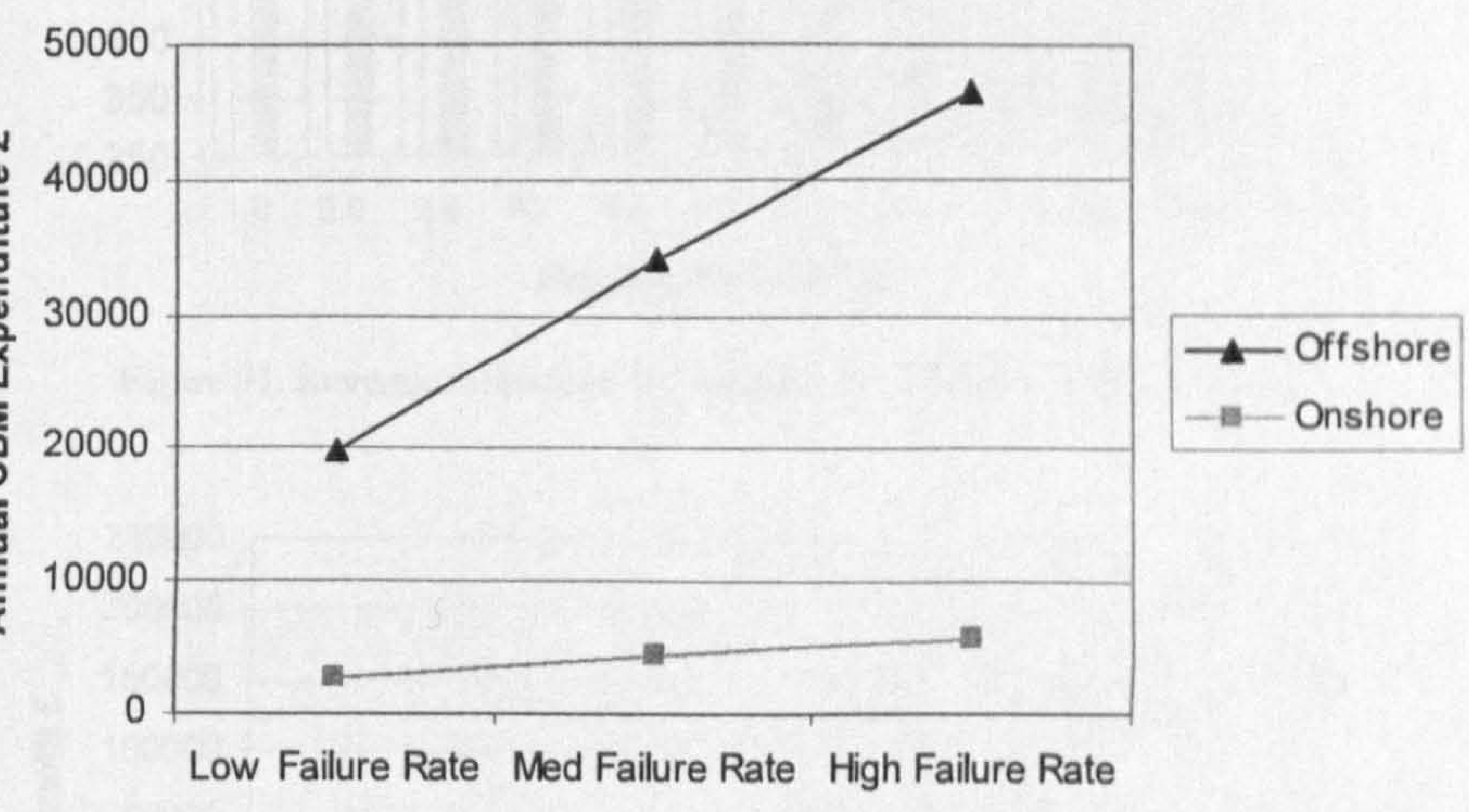

Figure 90: Comparison of Annual CBM Benefit for Onshore and Offshore Models

6.1.5 Reparability of Components

The reparability analysis was carried out in a similar manner to the onshore case presented earlier in the thesis. The revenue trend (see Figure 91) is similar to that observed for onshore results. The revenue associated with a CBM policy is still far less sensitive to repair probability than TBM. Figure 92 shows that TBM becomes the most cost-effective policy if more than 60% of reactive maintenance actions do not require a component replacement. This is substantially different to the equivalent onshore result (see Figure 65) which showed TBM becoming cost effective at over 0.8 repair probability (20% higher). This means that for offshore conditions, it only makes sense to employ CBM if components cannot be repaired after failure rather than replaced. If the probability of repair is less than 0.6, offshore CBM makes economic sense.

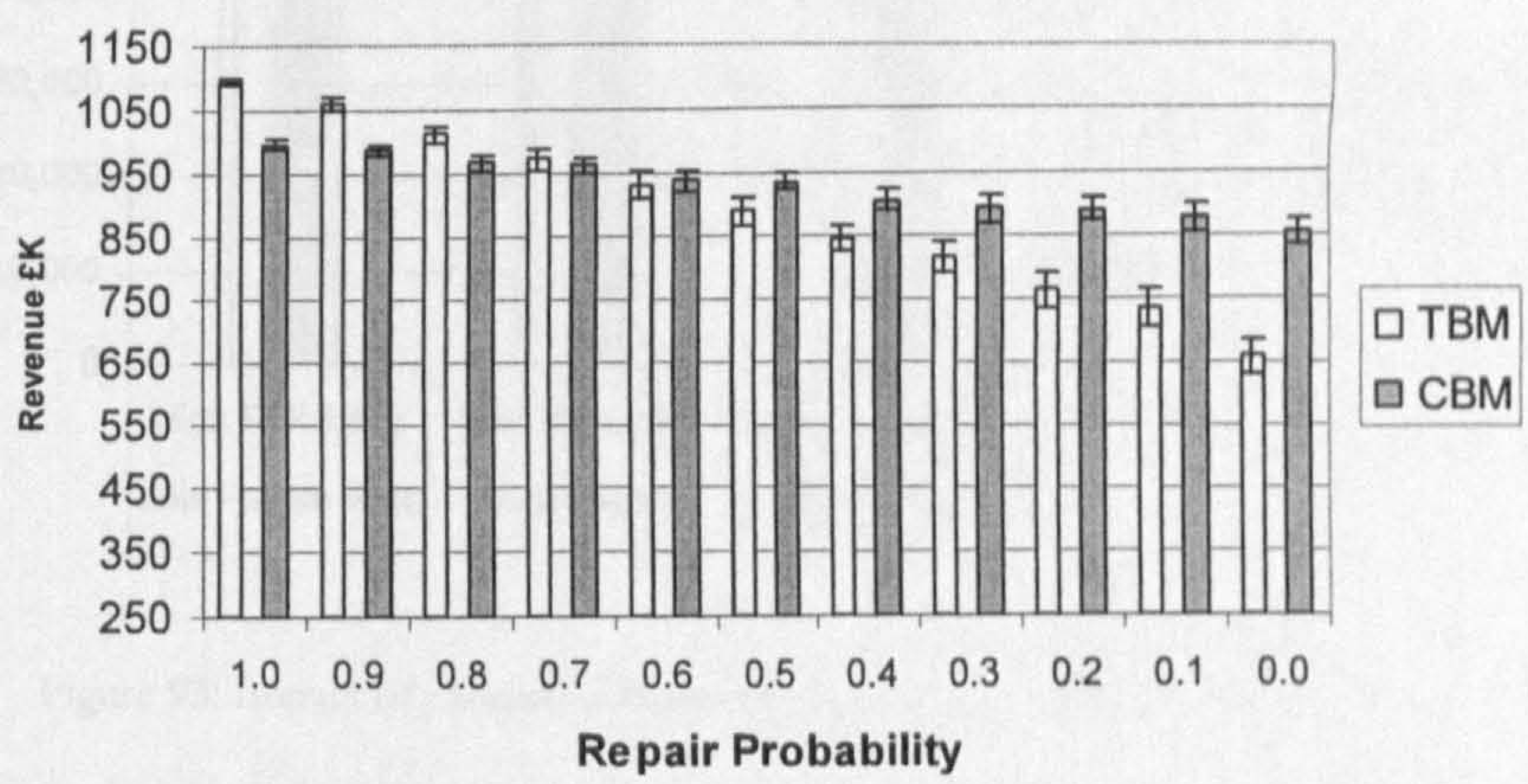

Figure 91: Revenue Impact of Reparability for Offshore TBM & CBM

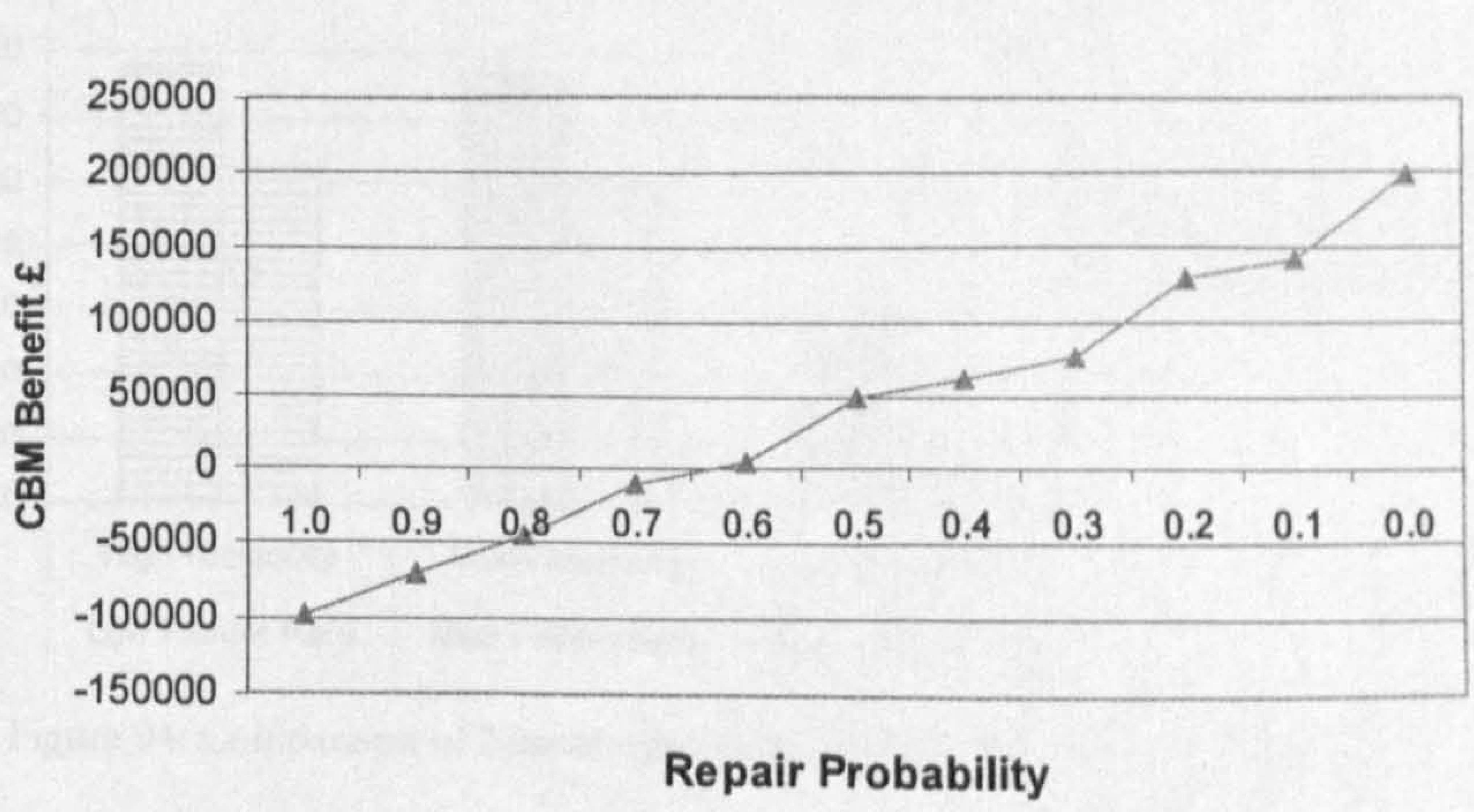

Figure 92: Reparability Impact on Offshore CBM Benefit

6.1.6 Impact of Maintenance Action Costs

The estimated cost for offshore crane mobilisation (£15,000) is added to the hire cost for a single maintenance action resulting in an increased estimate of C_{EQ} to £30,000, effectively doubling the base case offshore maintenance costs (see Table 46). Figure 93 shows the net CBM benefits for high, medium and low WT reliability (for increased maintenance costs). These benefits are directly compared to the offshore base case in Figure 94: the figure suggests that doubling the maintenance cost has a significant negative effect on offshore CBM benefit, particularly the low reliability level when the CBM benefit becomes only marginal.

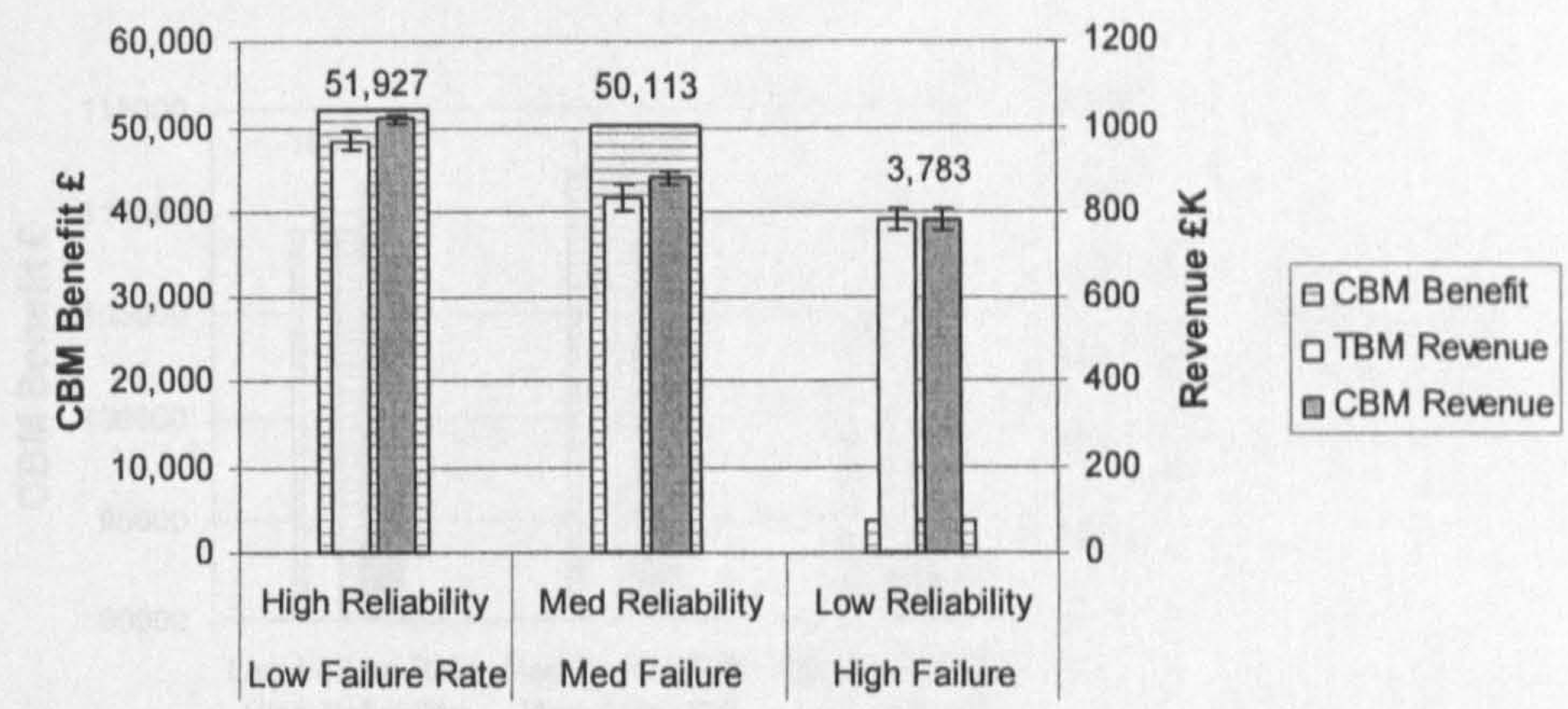

Figure 93: Impact of Increased Maintenance Costs on TBM & CBM Revenue

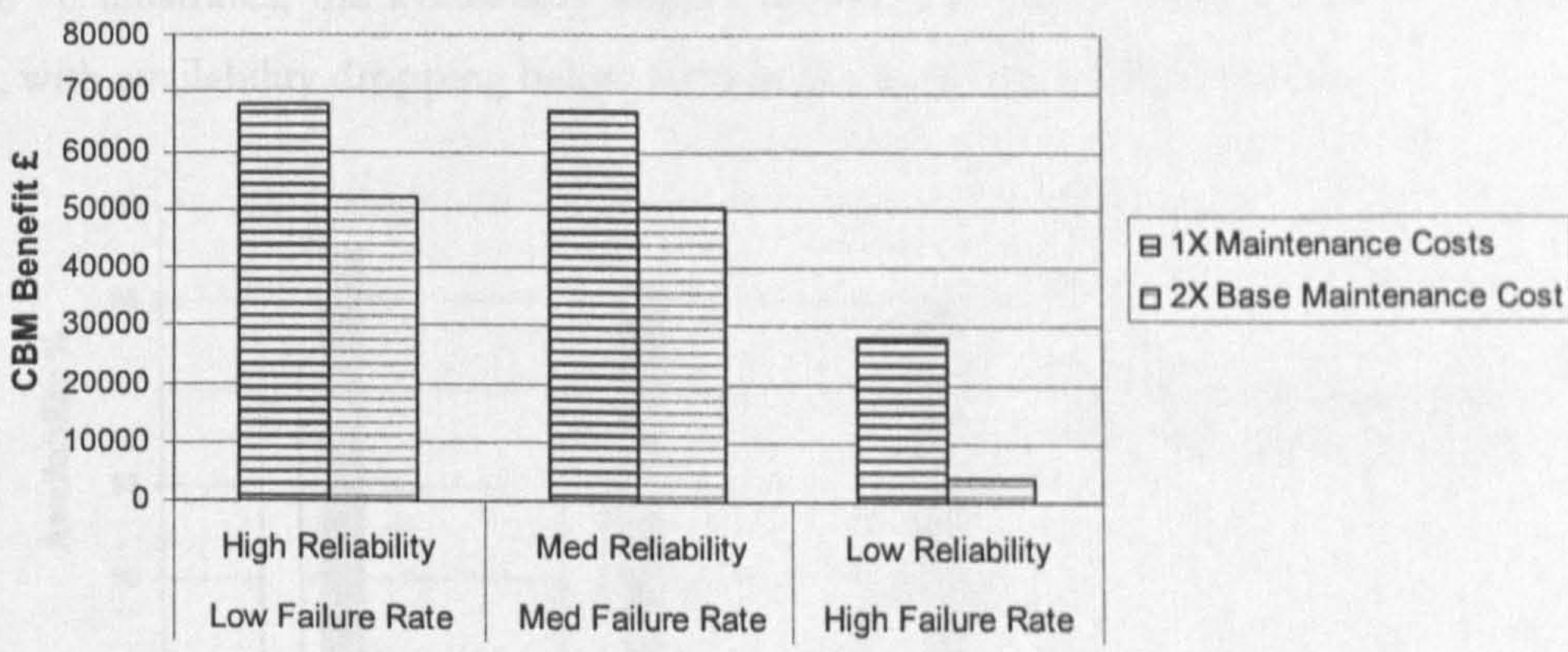

Figure 94: Comparison of Maintenance Cost Impact on Offshore CBM Benefit

6.1.7 Impact of Downtime Variation

It is unrealistic to expect that the unplanned downtime for offshore failures would reduce to levels below those presented in Table 46 (41 days for gearbox and rotor blade, 32 days for generator). Therefore the more conservative downtime estimates used in the equivalent onshore section cannot be used. Instead, the values presented by Andrawus et al. (2006) (see Table 44) are adopted, which represent a more pessimistic view of downtime duration (downtime 120 days gearbox, 60 days generator, 120 days rotor blade, E&E held constant at 2 days). Figure 95 shows that the impact of these pessimistic downtime durations is to drive up CBM benefit in all reliability categories.

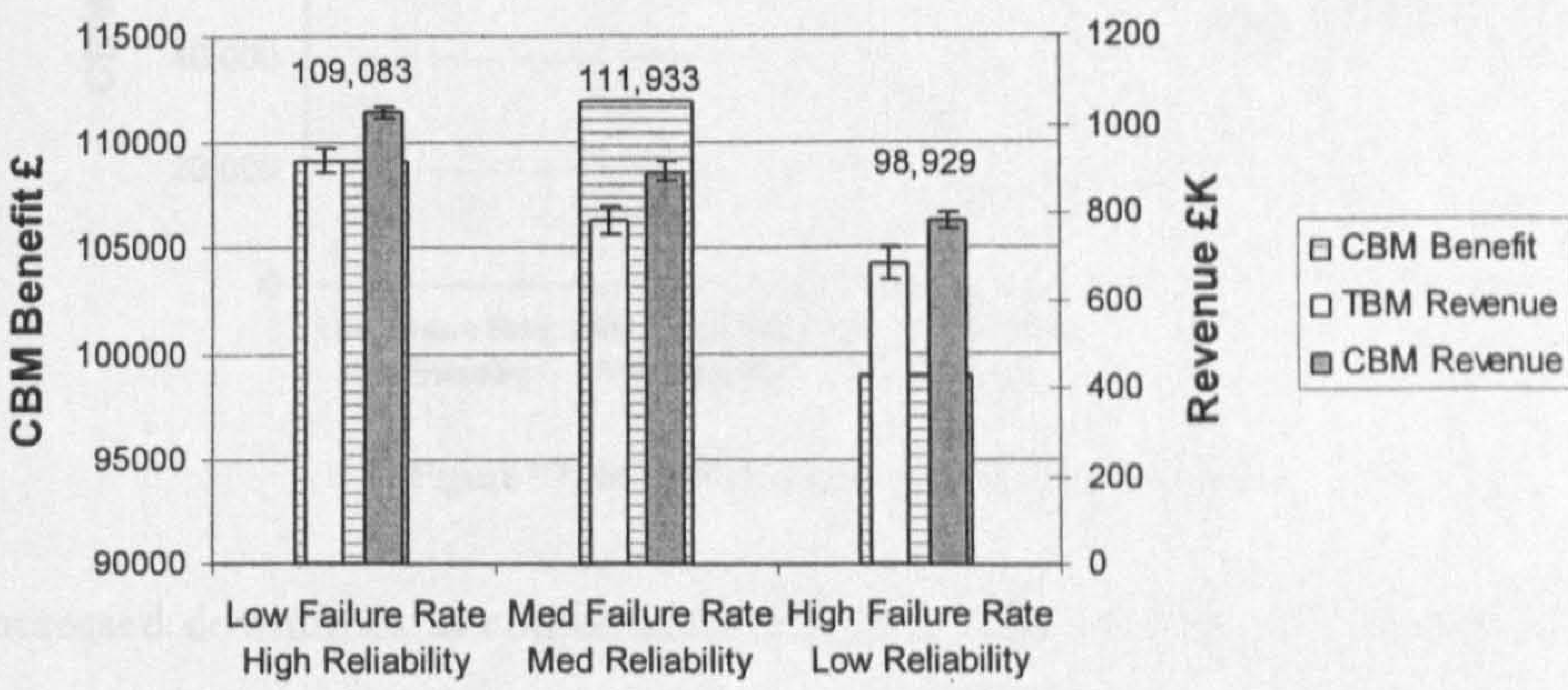

Figure 95: Impact of Downtime on TBM & CBM Revenue

It is also worth noting the severity of the availability impact of the increased downtimes. As Figure 96 illustrates, the availability impact for the TBM policy is much more severe than CBM, with availability dropping below 85% in the worst case TBM scenario.

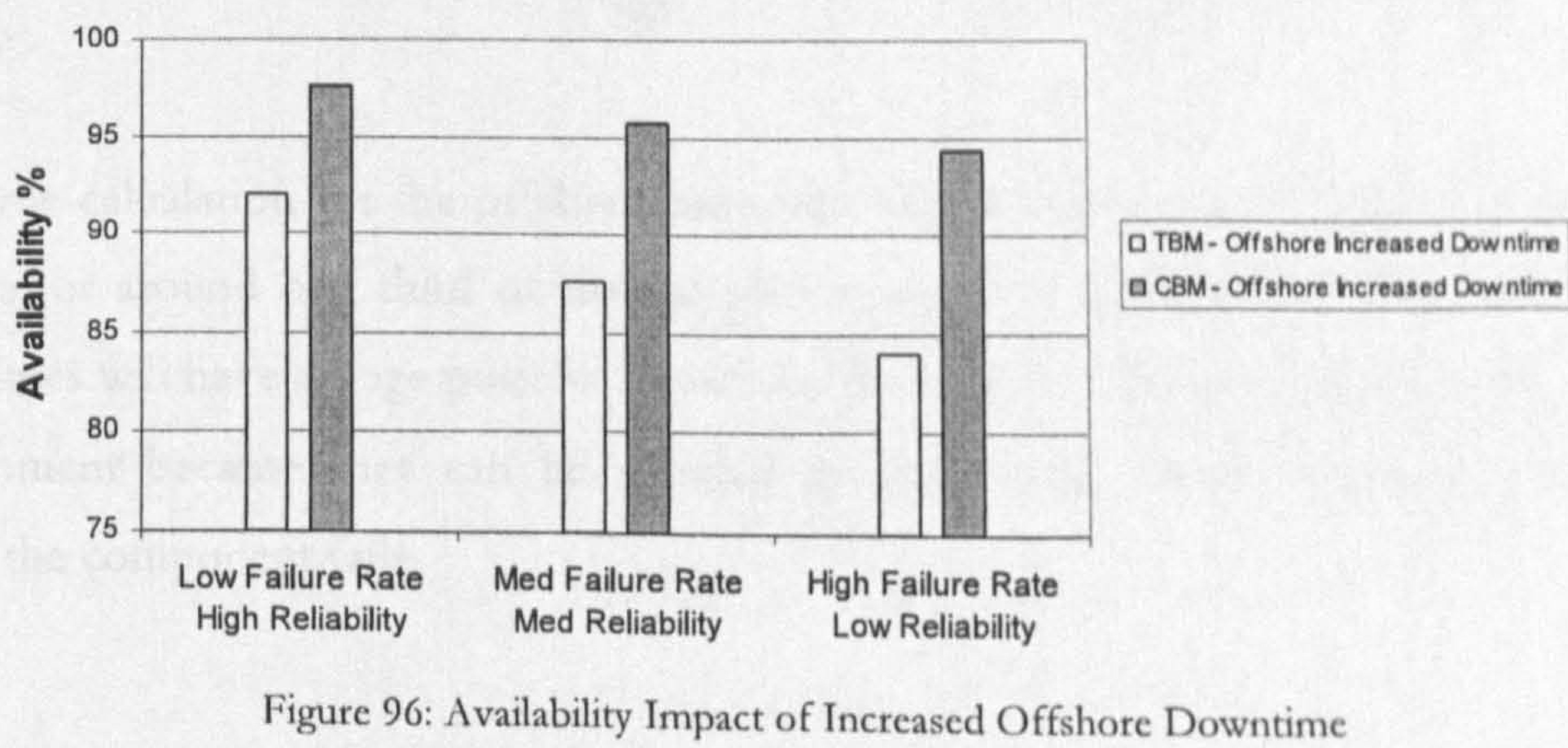

Figure 96: Availability Impact of Increased Offshore Downtime

The economic benefit of CBM is driven upwards the under this high downtime scenario. Figure 97 clearly illustrates that the increased downtimes have a very definite positive impact on the economic case for CM, as compared with the offshore base cases. The reason for this large level of benefit can be thought out by considering a single major offshore outage event.

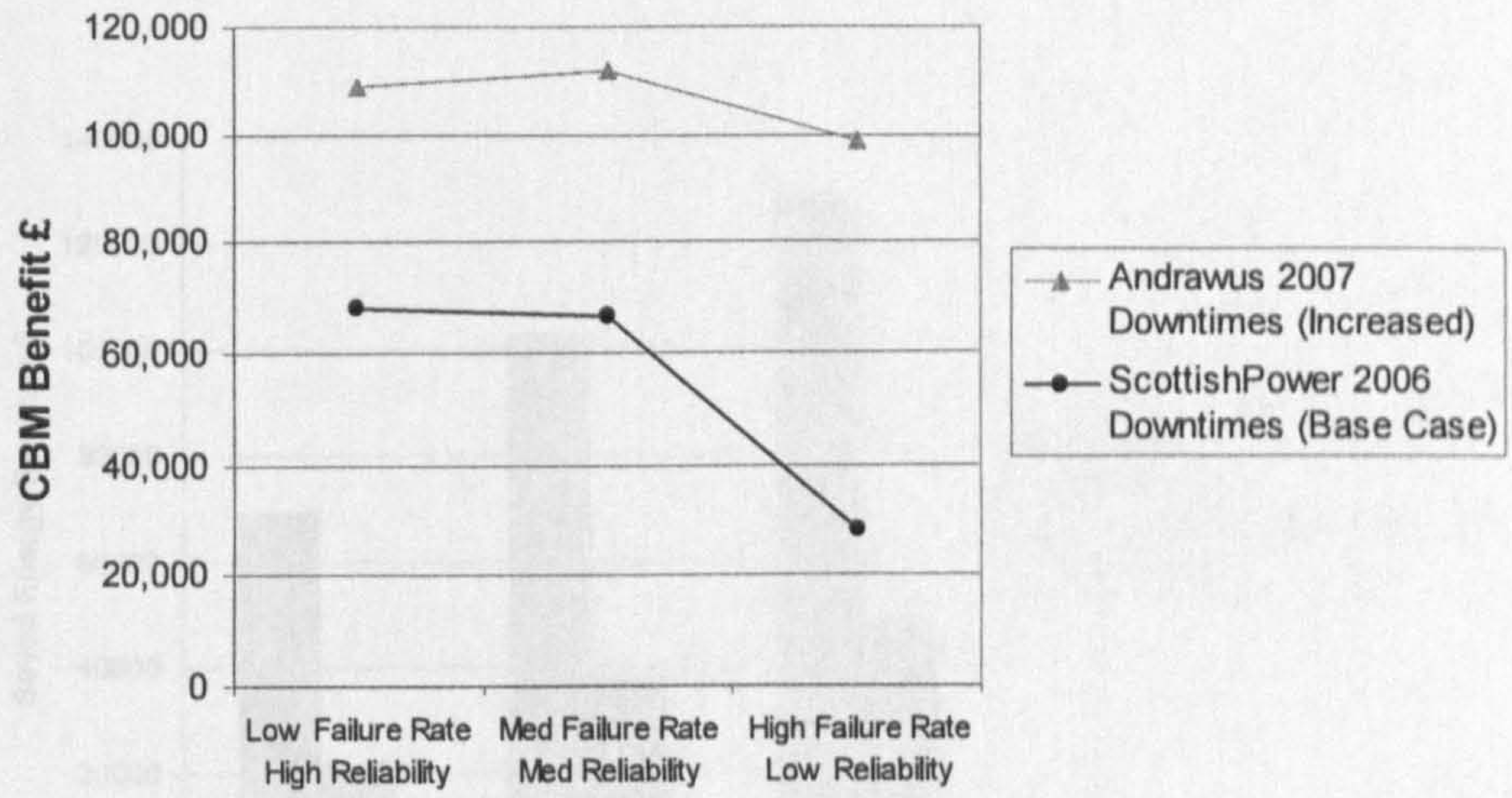

Figure 97: Impact of Downtime on CBM Benefit

The increased downtimes in combination with the 5MW offshore WT rating and increased number of offshore ROCs mean that, the consequences of an outage become very significant. For example, a gearbox outage of 120 days duration equates to lost revenue (R_{LOST}, calculated using equation 37) of nearly £400,000 – see calculation below.

$$R_{LOST} = Y_{ann} \times (MP_{ELEC} + MP_{ROC}) = \left(\left(\frac{120}{365} \times 8760 \right) \times 0.3 \times 0.95 \times 5 \right) \times (£36 + £60) = £393{,}984$$

The same calculation for the offshore base case would involve an unplanned downtime of 42 days, or around one third of the calculation above (~£130,000). Clearly the increased downtimes will have a huge positive impact on the case for CM deployment in the offshore environment because they can be avoided by performing condition based maintenance before the component fails.

The basic calculation above confirms that factors involved in offshore wind farms combine to increase the economic impact of major outage events so that as well as high downtime, the higher WT rating means that the cost of an outage increases very significantly. This is further reinforced by Figure 98, which compares the saved energy revenue of a CBM policy for both downtime estimates.

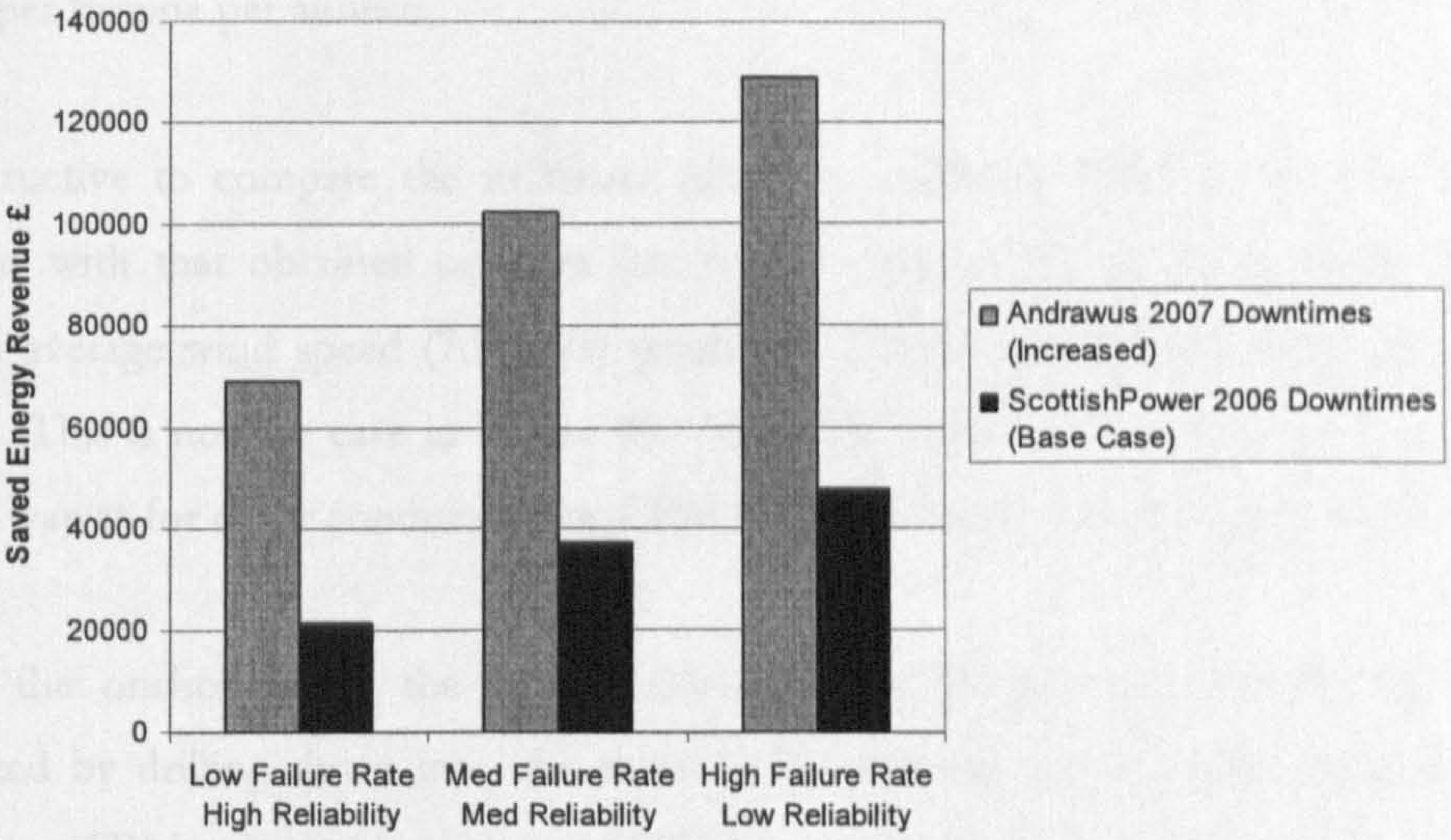

Figure 98: Offshore CBM Saved Energy Revenue Downtime Comparison

The increased importance of lost revenue for the increased downtime case results in the obvious coupling in Figure 97. This in turn demonstrates that increased downtime is a key enabler for adoption of CBM offshore.

6.1.8 Impact of Wind Regime

A stronger wind profile, expected to be encountered in the offshore environment, was adopted in this section as in section 5.1.8. The impact of the increase in wind regime on CBM benefit is shown in Figure 99 – this illustrates a significant increase in CM benefit for higher wind speeds, however the impact is not as great as the downtime increase in the previous section. The stronger wind profile boosts the CM benefit by between £10,000 and £28,000 per turbine per annum.

It is instructive to compare the influence of wind profile on CBM benefit for offshore conditions with that obtained onshore (see 5.1.8 – Figure 70). In the onshore case, the increased average wind speed (7.95m/s) resulted in CBM benefit increasing with reducing reliability. This is not the case in Figure 99 – the CBM benefit is coupled with reliability in the same way as for other conditions (i.e. CBM benefit reduces with reducing reliability).

As with the onshore case, the factors driving the CBM benefit characteristic can be investigated by drilling down into the result and examining the revenue gained via saved energy (for a CBM policy) minus incurred CBM costs: this is shown in Figure 100.

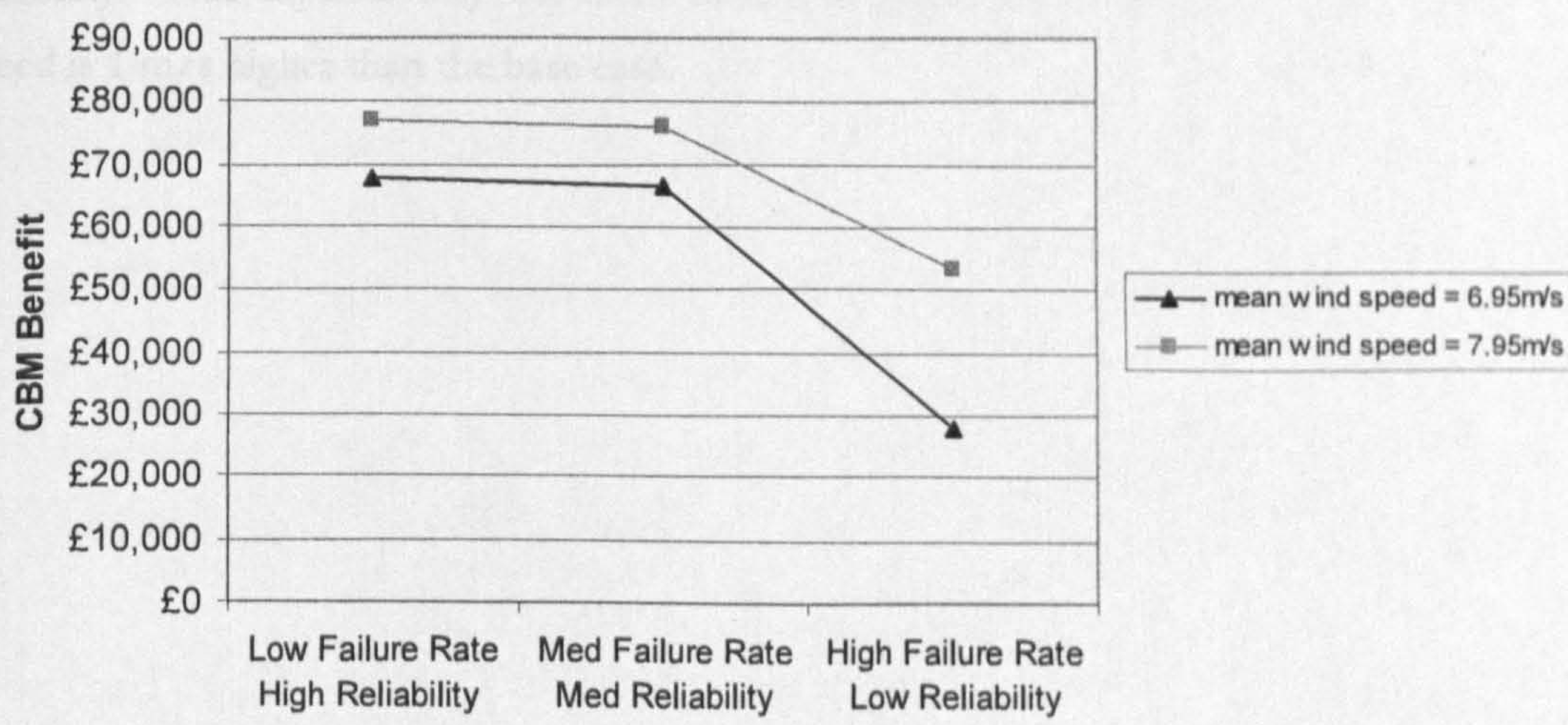

Figure 99: Impact of Wind Regime on Offshore CBM Benefit

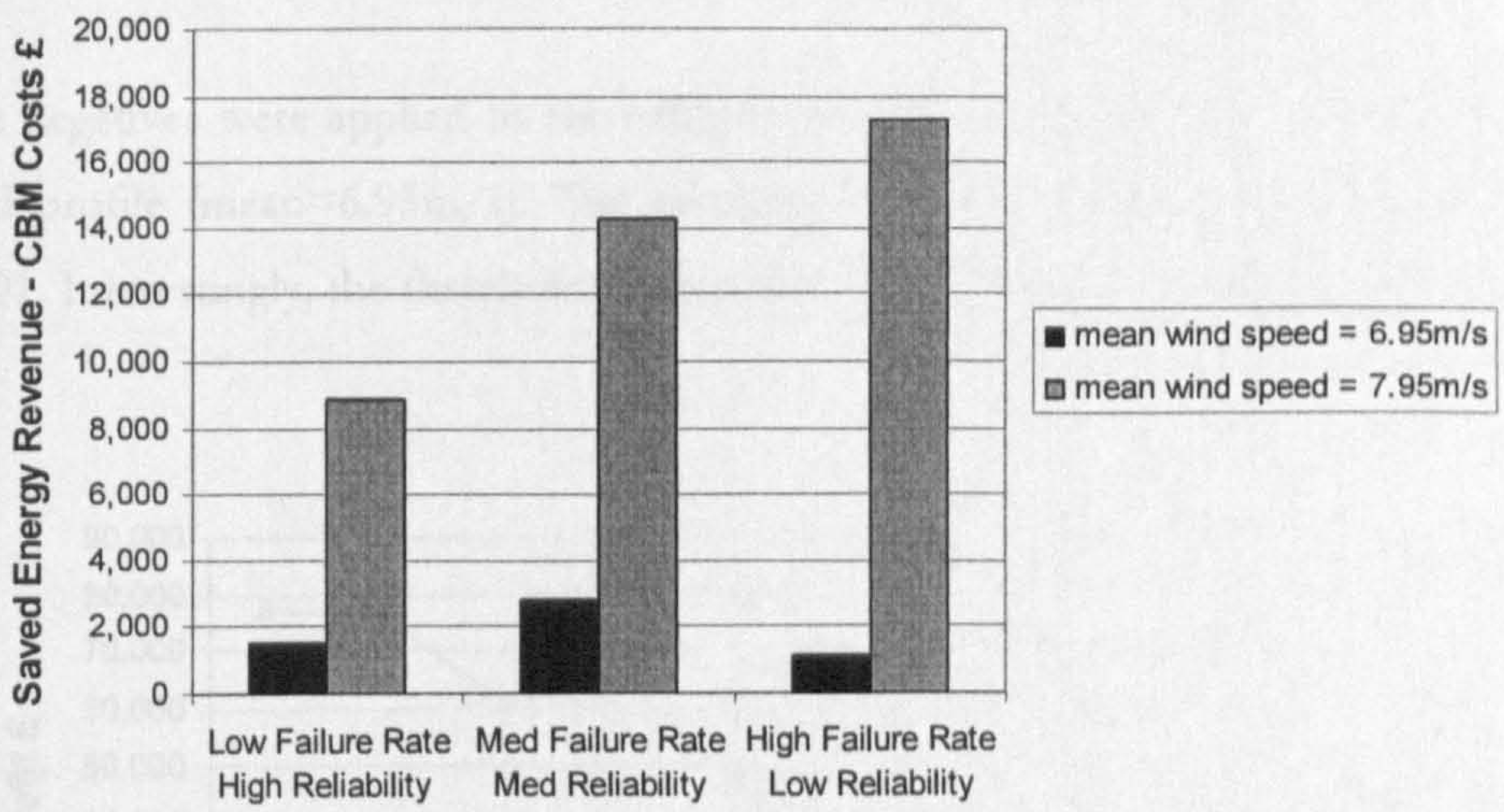

Figure 100: Offshore Saved Energy Revenue as a function of Wind Profile and Reliability Level

Figure 100 illustrates that for the lower wind profile (mean 6.95 m/s), the saved revenue grows larger than maintenance costs until the low reliability level is reached. At this point the incurred costs of maintenance are more influential than the saved revenue.

For the high wind profile (mean 7.95 m/s), the saved energy revenue is always greater than the incurred maintenance costs, indeed the positive difference grows with decreasing reliability. This explains why the CBM benefit is significantly increased if the mean wind speed is 1 m/s higher than the base case.

6.1.9 Imperfect Condition Monitoring Diagnosis Impact

CM false negatives were applied to the offshore model for medium levels of reliability and low wind profile (mean=6.95m/s). The resultant impact on CBM benefit is illustrated in Figure 101. Interestingly, the threshold for positive CBM lowers from 0.5 (onshore) to 0.2.

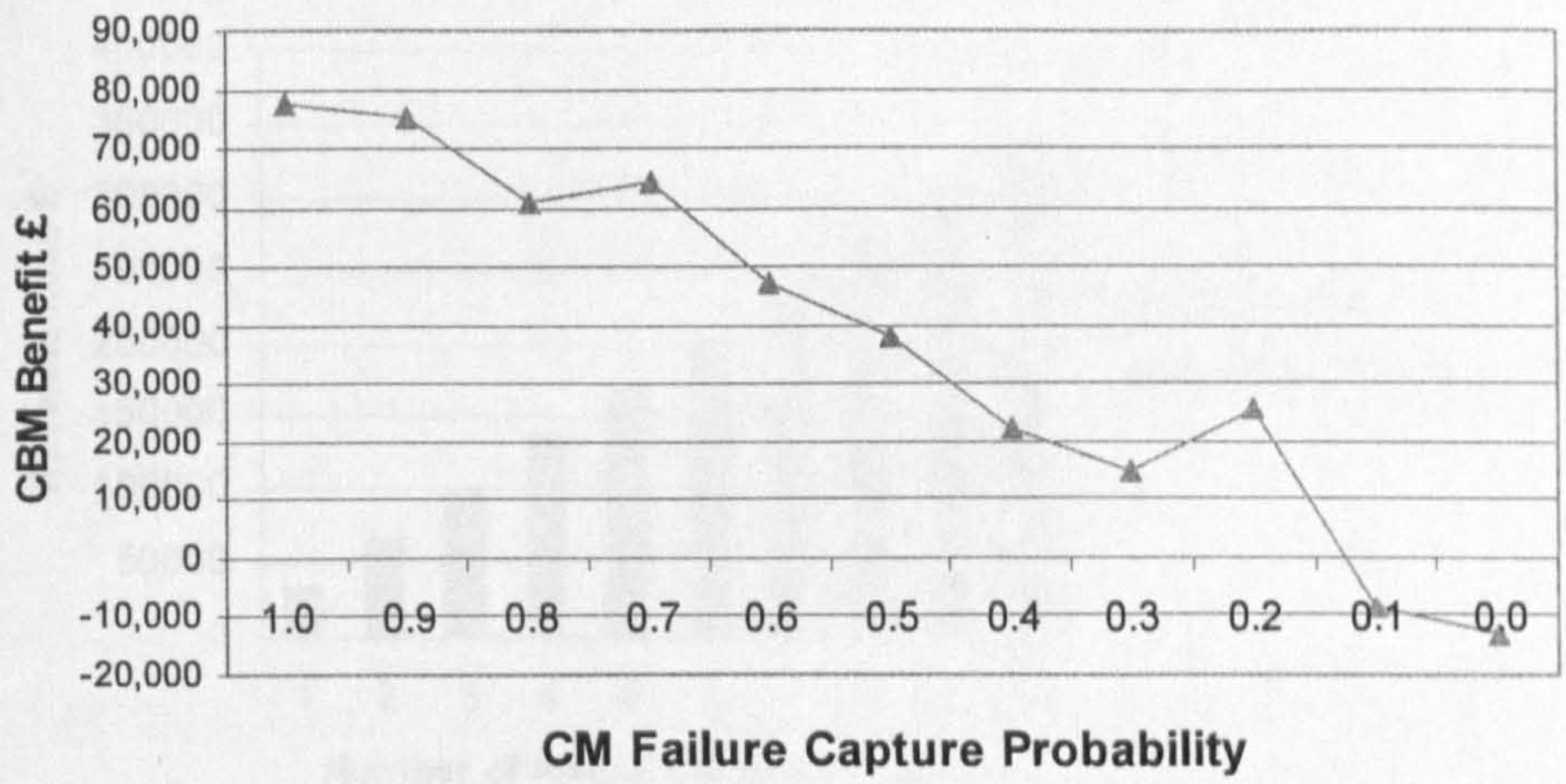

Figure 101: Revenue Impact of CM False Negatives (Offshore)

This means that the system does not require such a high level of performance as in the onshore case as regards false negatives because the potential savings are greater for each component outage event. The figure of 0.2 is especially pertinent as anecdotal experience suggests that the current performance level of modern WT CM systems is around 30% incipient failure detection – 0.3 (Reviewer, Wind Eng paper). Although some of the results in this chapter call into question the economic viability of CBM offshore (see section 6.1.6, low reliability scenario) the result in Figure 101 demonstrates that offshore conditions indeed tip the balance in favour of CBM, even when real-world problems with CBM (in the form of false negatives) are factored in.

False positives were implemented in the same way as for the onshore case. The contribution of lost energy and spurious CBM actions to the lost revenue is quantified in Figure 102. Comparing this with the onshore case (see Figure 74) shows that the proportion attributable to lost energy is significantly higher than the onshore case, which is intuitive given the 5MW rating and offshore wind profile. Although the source and magnitude of the contributions to lost revenue change for offshore conditions, the threshold at which CBM becomes uneconomic as a result of false negatives is the similar as for onshore (3 false positives per annum – see Figure 103, as opposed to 4 onshore). This result is counter-intuitive, given the significant impact of offshore conditions on false negatives - Figure 103 suggests that the balance of incurred maintenance costs and lost energy does not change.

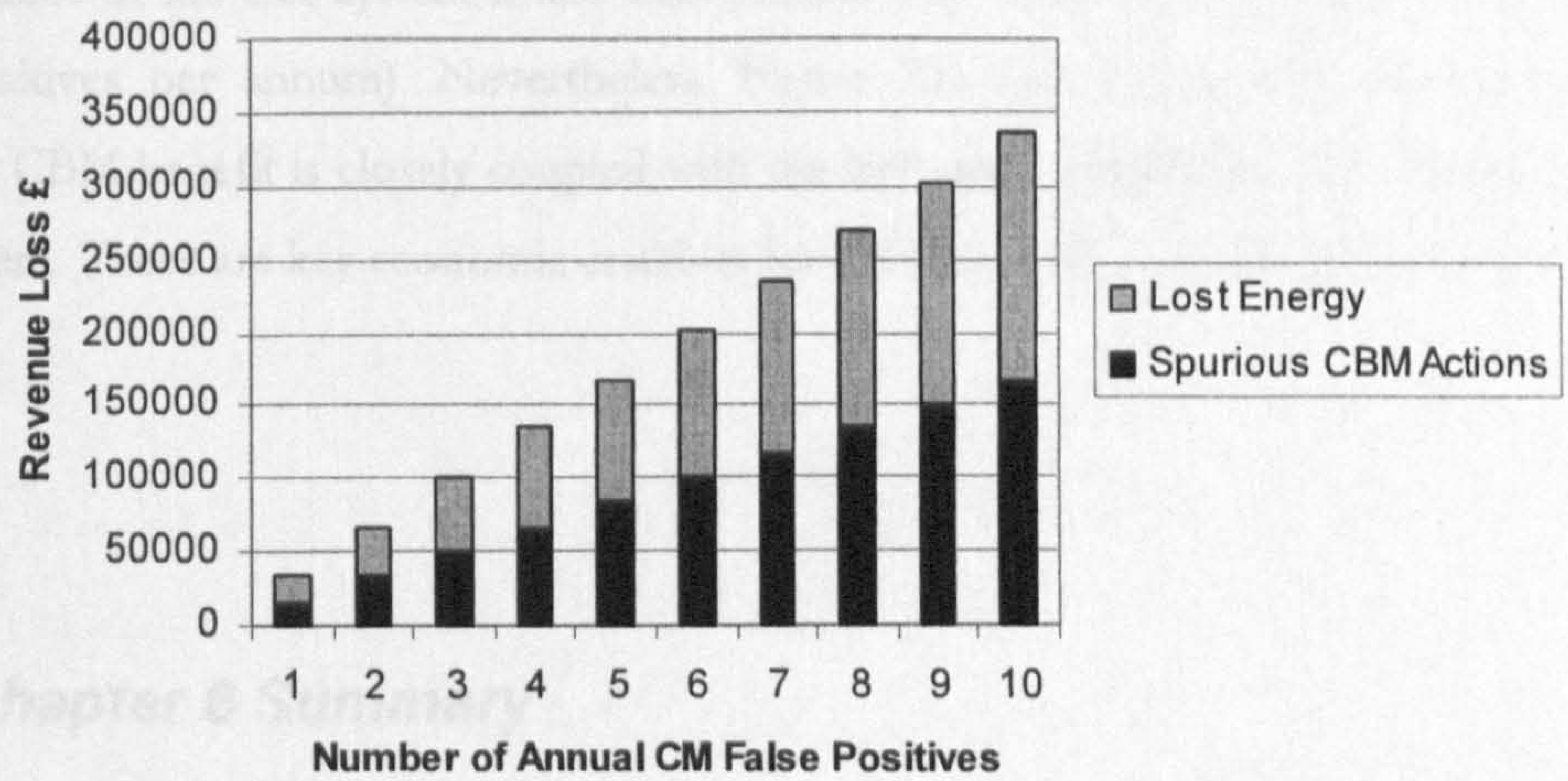

Figure 102: Economic Impact of CM False Positives – Offshore

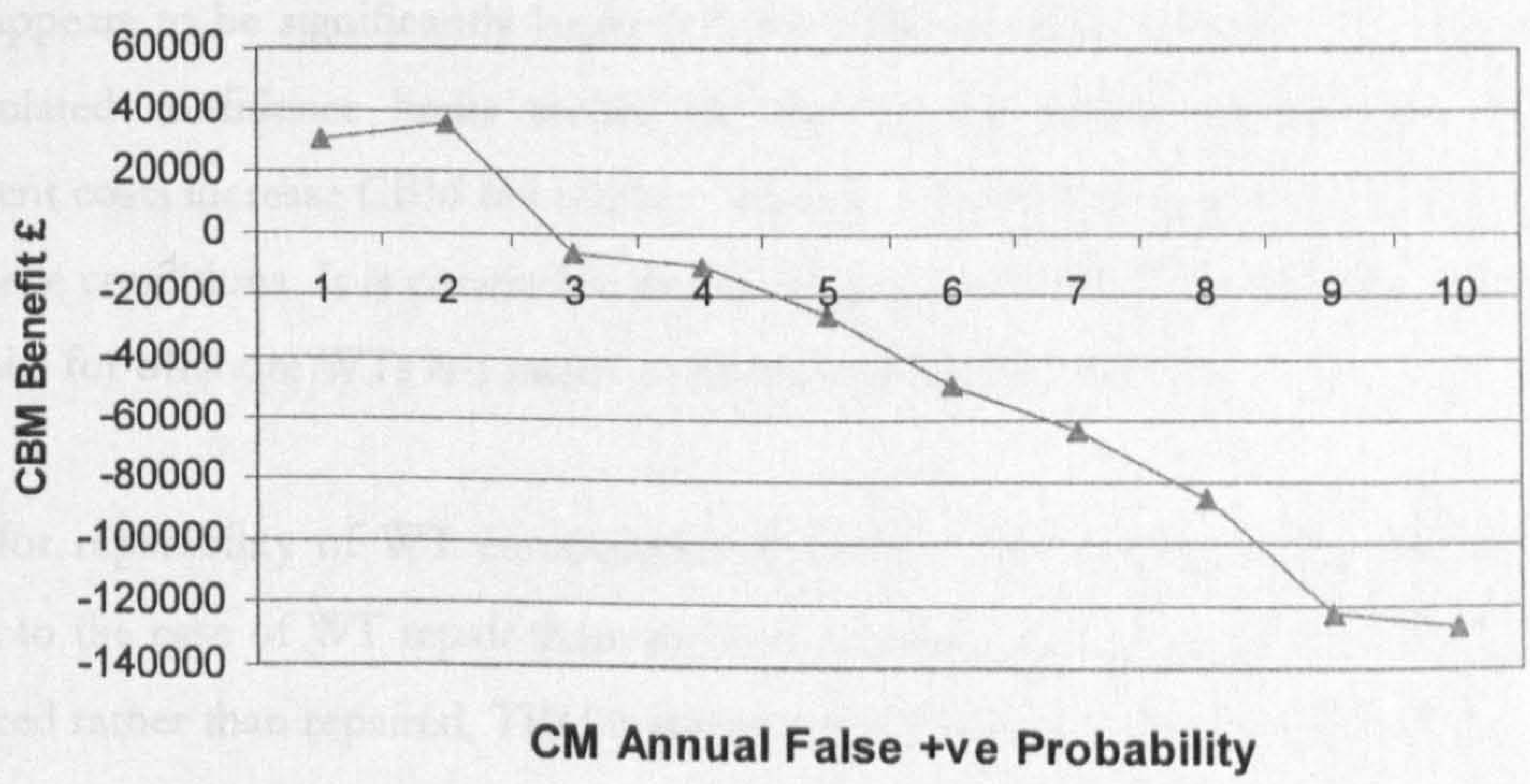

Figure 103: Impact of CM False Positives on CBM Benefit – Offshore

Therefore a key conclusion of this research is that offshore conditions do not require such high technical capability to be economically viable as onshore, in terms of failure detection probability (false negatives) since the potential savings are higher – in terms of lost energy and component repairs. These benefits outweigh the incurred cost of more frequent maintenance actions associated with CBM, and in many cases the benefit is clear even if the performance of the CM system is less than perfect (e.g. down to 20% failure detection & 2 false positives per annum). Nevertheless, Figure 101 and Figure 103 demonstrate that offshore CBM benefit is closely coupled with the technical capabilities and robustness of the CM system. These are key economic enablers for CBM regardless of the local constraints.

6.2 Chapter 6 Summary

The offshore WT model was investigated in this chapter. The results showed that the offshore WT model produces lower overall WT availability but higher energy yields, annual revenue, WT failure rates and lost energy than the onshore WT model. Base case WT CBM benefit appears to be significantly larger (x2) for offshore WTs, however the magnitude of the calculated confidence limits makes the size of the benefit unclear. Increased WT component costs increase CBM benefit by ~4 times. This compares with a ~2 times increase for onshore conditions. It is concluded that the higher cost of WT component replacements and repairs for offshore WTs is a major enabler for offshore WT CM.

Results for reparability of WT components show that the offshore CBM benefit is more sensitive to the ease of WT repair than onshore. If only 30% or less of WT failures have to be replaced rather than repaired, TBM is more cost-effective for offshore WTs than CBM.

Doubling WT maintenance action costs (specifically, crane hire mobilisation costs) has considerable effect on CBM benefit. CBM benefit across all WT reliability levels is reduced, and CBM benefit is marginal for the low WT reliability, high maintenance cost scenario.

Downtime increase has large impact on results, clearly tipping the balance in favour of CBM. It has been shown that the 'lost energy' component of CBM benefit is driving this impact. Thus, high WT downtimes for unplanned outages offshore make a persuasive case in favour of CBM, particularly for WTs with low reliability.

Increase in the mean wind speed (mean=7.95m/s instead of 6.95m/s) boosts the case for CBM over all WT reliability levels. However, it is not as influential as the WT downtime increase previously mentioned.

Finally, the threshold for positive WT CBM economic value in terms of technical capability of the CM system (false negatives) decreases from ~30/40% (onshore) to ~10/20% (offshore). Onshore systems require higher levels of CM technical performance in order to justify themselves economically. Relatively error-prone CMS can still be more cost-optimal than TBM in the offshore environment, because the potential cost savings are very significant. Surprisingly, the result as regards false positive threshold at which CBM becomes uneconomic is similar in onshore (3 false positives per annum) and offshore (4 per annum) conditions.

In this chapter, the benefit of CM applied to offshore WTs was evaluated. The final chapter of this thesis summarises the key findings of the results in chapters 5 and 6, and discusses the implications of these results in detail.

6.3 Chapter 6 References

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7 Discussion, Conclusions and Further Work

It has been established that the models presented in this thesis can quantify the technical and economic benefits of CBM relative to a TBM policy, thus establishing if a techno-economic case for CM applied to wind farms exists in practice (A theoretical case can be made despite the differences between wind farms and thermal plant as outlined in chapter 2). The proposed models have been validated by comparison of the outputs with other literature sources and verification of the operation of the model.

In some cases the results challenge the theory that CBM is the most cost-effective maintenance policy for wind turbines, having taken operational and practical issues into account. It is interesting to note that in most cases a very clear case for CM exists if it is assumed that the CM system can detect every failure and does not produce false positives – this is an implicit assumption in almost all of the existing literature attempting to benchmark techno-economic performance of CMS (e.g. Ribrant & Bertling 2007) – however it must be noted that the practical experience of wind farm operators indicates that the performance of existing WT CM systems falls well short of this idealised scenario. The analyses produced in this thesis show that the performance of the CM system has an important influence on the value of CM, and that if the technical performance of the CM system is poor, that this can undermine the case for CBM applied to WTs.

The models in this thesis have gone beyond such rather naïve assumptions to fully quantify the benefit of WT CM. The following sections describe the conclusions that have been arrived at as a result of the analyses of technical and economic benefit of CM contained in chapters 5 and 6. As well as visualising the particular condition-specific techno-economic benefits, a set of more generic 'conditions for success' have been formulated to guide prospective operation & maintenance policy decisions.

6.1.3 Increased Component Costs

The WT sub-component costs were increased according to the proportions derived from Sterzinger & Svrcek (2004) assuming capital costs of £5m for a 5MW WT. The absolute costs and multiplication factor increase are shown in Table 51. The impact of this change on the offshore maintenance policy cost-effectiveness is displayed in Figure 87.

The primary result of the increase in component cost is that CBM benefit increases from £14,292 to £76,595 annually. This is a very significant increase – approximately 5 times the base CBM benefit. This compares with a ~2 times decrease for the same experiment run under onshore conditions (see 5.1.3).

Therefore the conclusion reached for this offshore study is that increased component costs are an important enabler for offshore CBM. In the offshore case this is even more pronounced, as the results show. For this reason, raw material price, manufacturing capacity and global demand for turbines could have an indirect influence on maintenance policy.

Component Cost	McMillan & Ault 2007	Sterzinger & Svrcek 2004	Multiplication Factor
Gearbox	£400,000	£1,050,000	2.625
Generator	£200,000	£850,000	4.25
Rotor Blade (1)	£300,000	£466,666	1.555556
E&E	£20,000	£10,000	0.5

Table 51: Component Costs for 5MW Offshore Wind Turbine

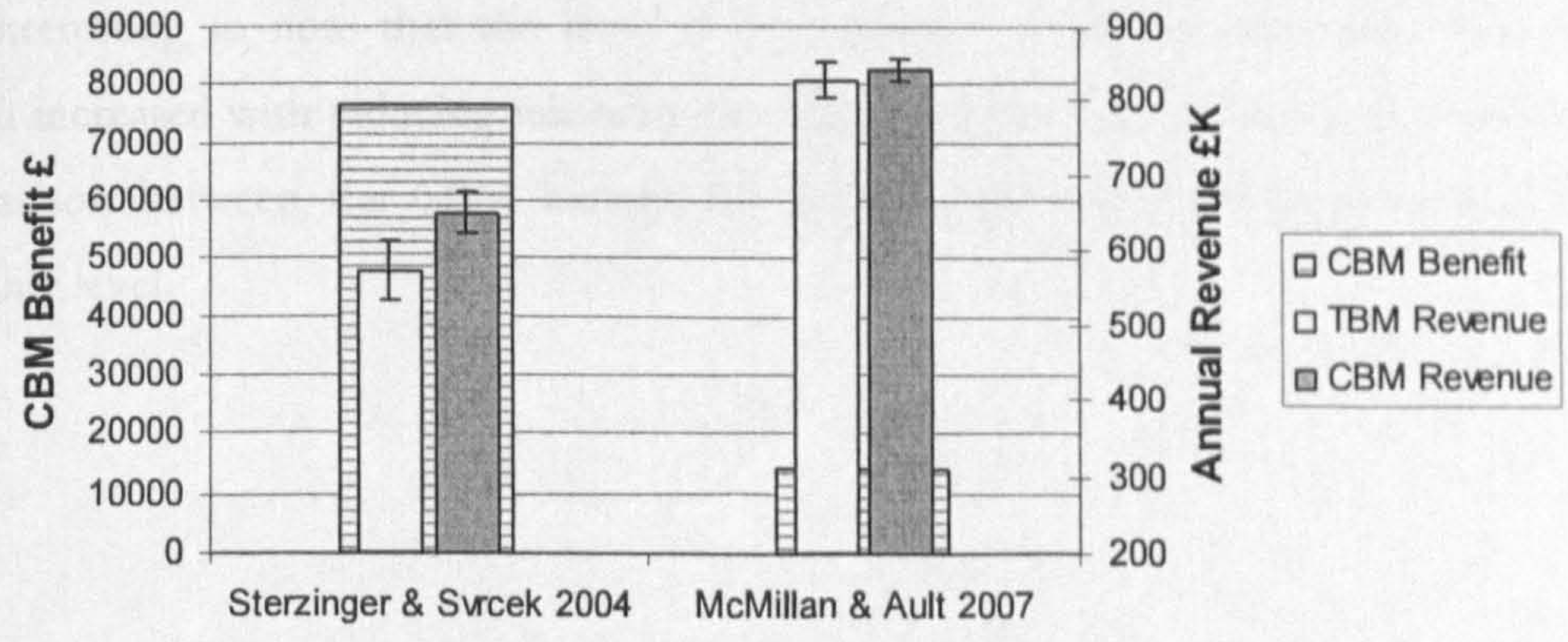

Figure 87: Offshore Revenues for Increased Component Costs

7.1 Onshore Wind Turbine Model Results

7.1.1 Economic Impacts of Model Input Assumptions

The sensitivity of the economic impact on the case for CM applied to wind turbines can be evaluated by examining how the CBM benefit changes as the input parameters vary. Figure 104 summarises the CBM economic benefit for a range of model input scenarios (carried out in chapter 5) enabling a direct comparison of results. Thus it is visualised, for example, that the combination of increased wind plant maintenance costs and low WT component reliability results in a low economic benefit. Similarly, low downtimes and high reliability will yield modest CBM benefit.

The largest benefit is realised for the combination of increased annual wind speed and low WT reliability. Increased maintenance costs coupled with high WT reliability also produce a high level of CBM benefit.

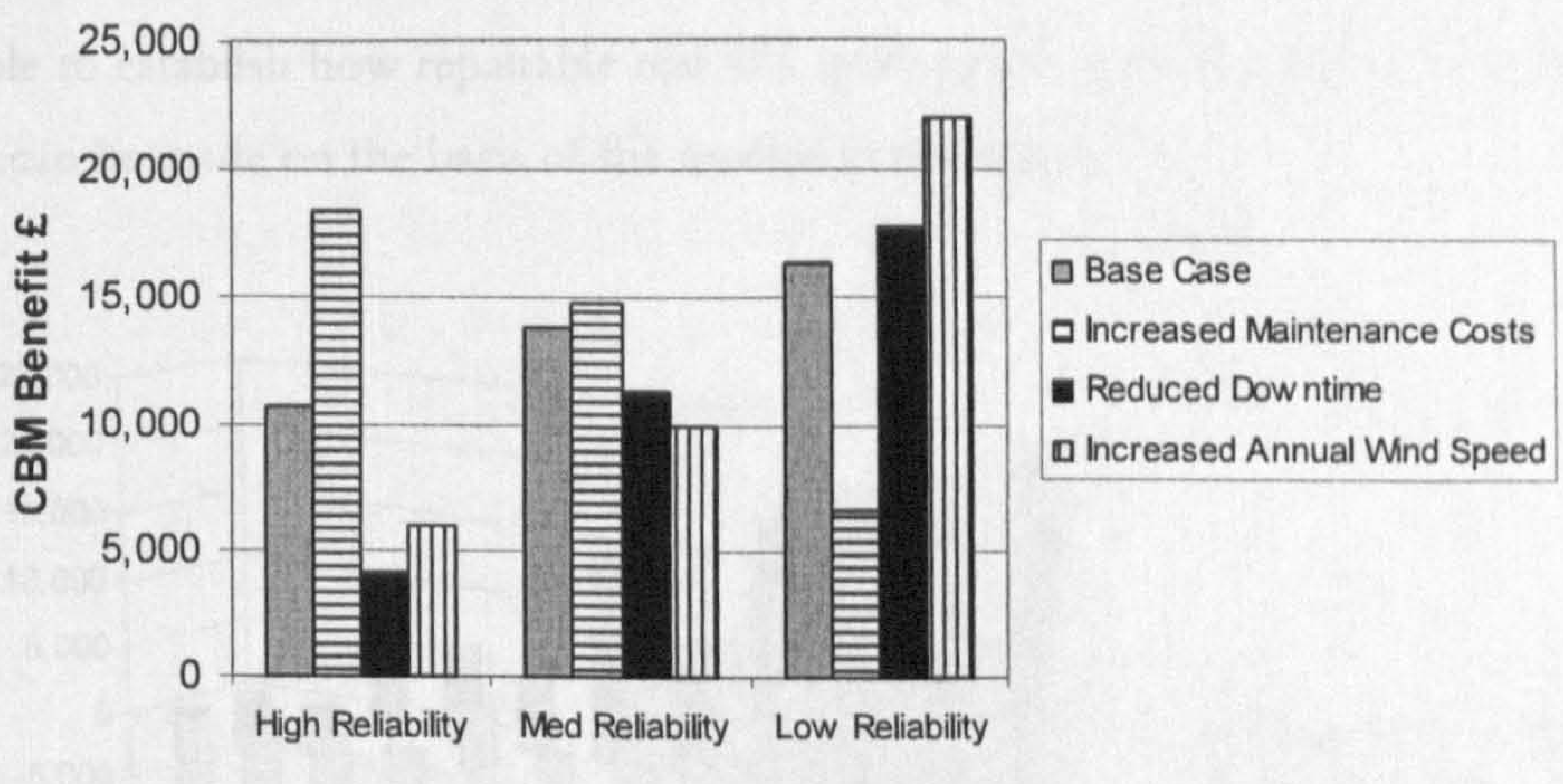

Figure 104: Impact of Model Parameters on Economic CBM Benefit – Onshore

The trend for most of the onshore WT results in Figure 104 shows CBM becoming more cost-effective as the WT reliability decreases. This applies for the base case, reduced downtime and increased annual wind speed. In these cases, the benefits of CBM (reduced amount of downtime, increased energy yield, and overall WT reliability improvement as a result of the CBM policy) grow faster than the incurred costs of maintenance.

The only scenario which reverses this trend is the case where the cost of individual WT maintenance actions is increased. In this scenario, the overall benefit of CBM is reduced because the costs of the incurred condition-based maintenance actions grow faster than the economic benefits induced by CBM.

Similar visualisation can be carried out for other input variables such as reparability and CBM false negatives – see Figure 105. These results show that under certain onshore conditions, it makes more sense to adopt TBM than CBM (CBM benefit < 0). The 'CM failure capture probability' is a particularly pertinent variable because this shows the linkage between CBM economic benefit and the technical capabilities of the CM system. It is debatable that current WT CM systems can successfully classify the 30-40% or more of incipient faults necessary to enable cost effective onshore WT CM as shown in Figure 105.

Similarly for the reparability of WT components, if only 0-20% of outright failures require a component replacement rather than a repair action, it makes economic sense to adopt TBM rather than CBM. As more data on WT component failure events becomes available, it will be possible to establish how repairable real WT systems are, and whether an economic case for CBM can be made on the basis of the models in this thesis.

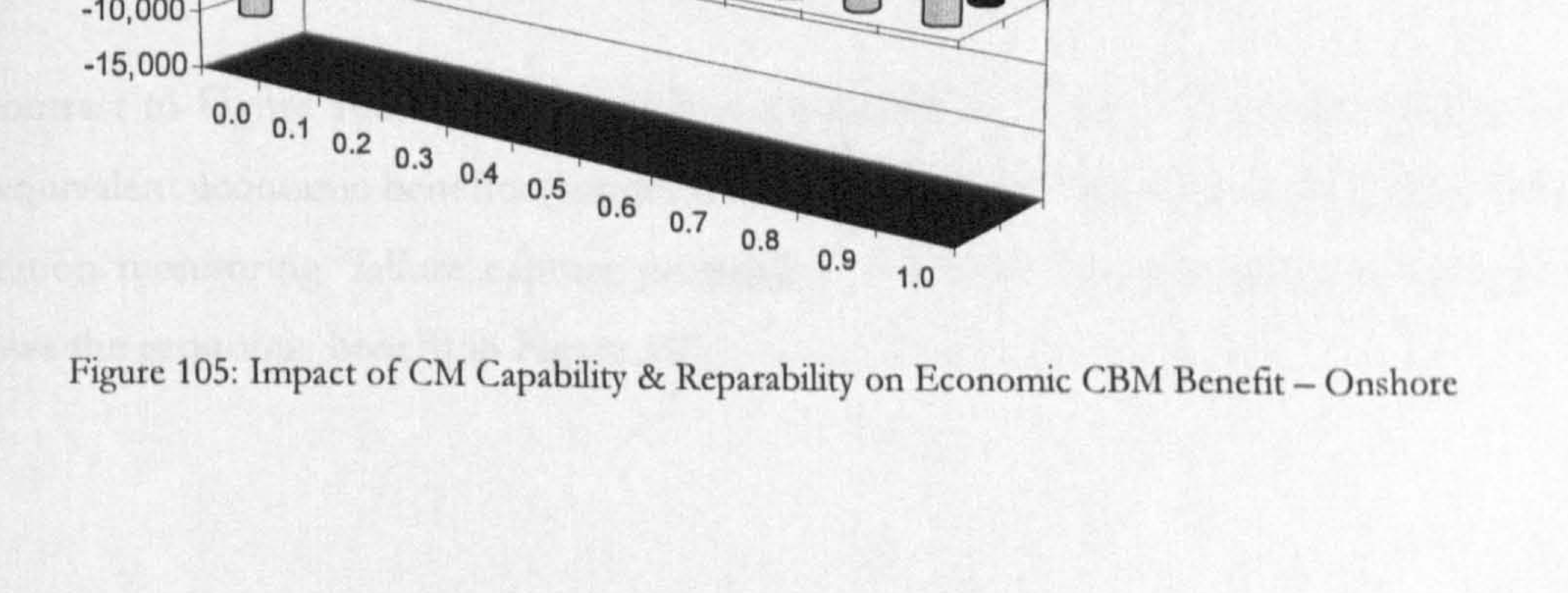

Figure 105: Impact of CM Capability & Reparability on Economic CBM Benefit – Onshore

7.1.2 Technical Impacts of Model Input Assumptions

The technical impact on the case for CM applied to wind turbines can be evaluated by examining any of the technical output metrics produced by the simulations. A key technical metric used to evaluate impact of O&M policy is the annual availability of the WT. This is plotted in Figure 106 and Figure 107.

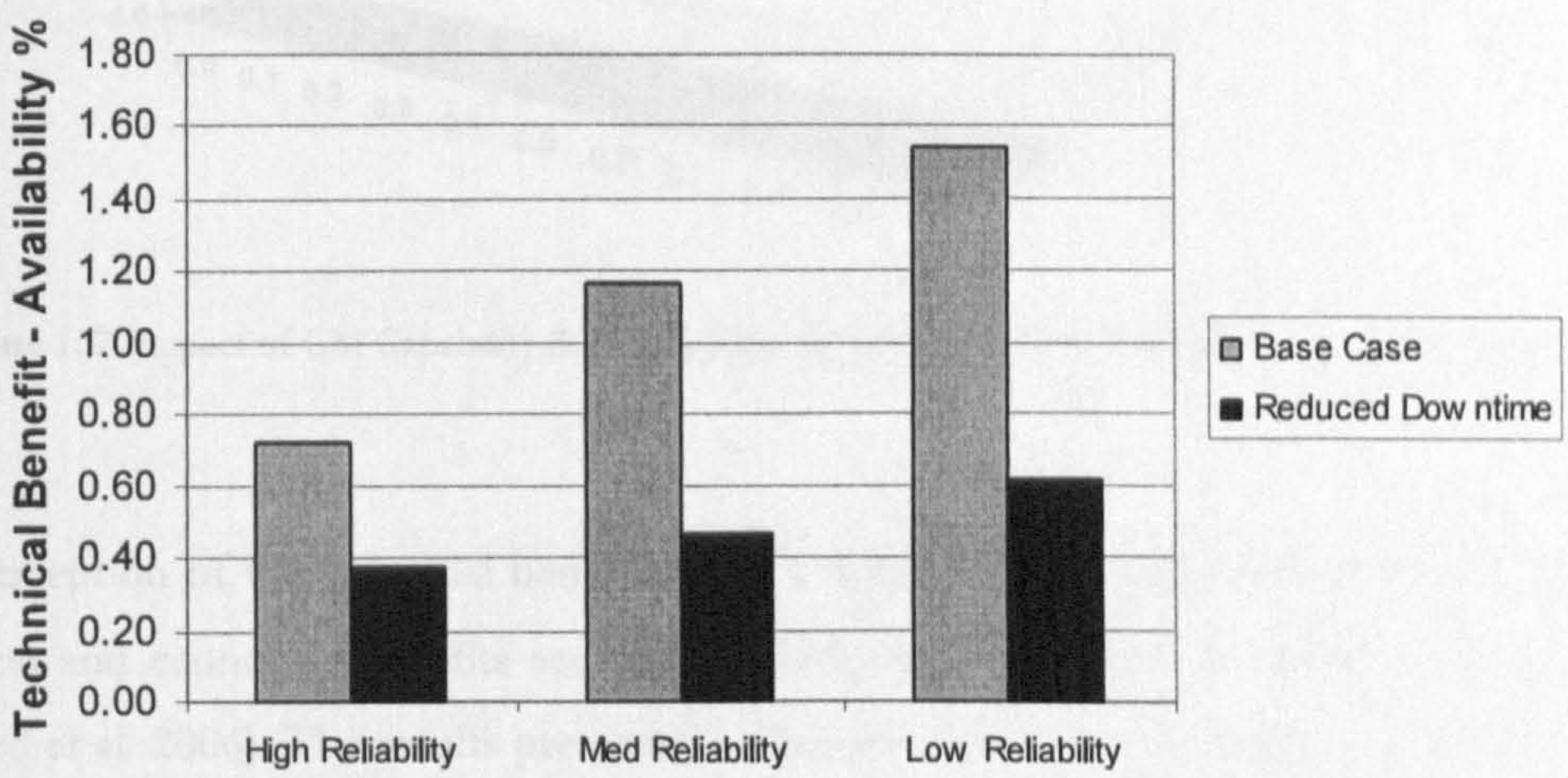

Figure 106: Impact of Model Parameters on Technical CBM Benefit – Availability Onshore

Figure 106 shows the availability impact of the base case and the reduced downtime scenario. It is clear that the CBM benefit of a WT with reduced downtime is not as sensitive to variation in reliability as the base case. Furthermore, the WT availability benefit associated with CBM is higher for the base case, because the adoption of CBM avoids more potential downtime in the base case. It is interesting to compare this with the equivalent economic benefit in Figure 104, which does not follow a similar trend to the technical benefit. This shows that the technical and economic benefits of onshore WT CBM are not always well aligned.

In contrast to Figure 106, the technical benefits shown in Figure 107 are well aligned with the equivalent economic benefits (compare with Figure 105). This is particularly clear for the condition monitoring 'failure capture probability' for which the availability benefit closely follows the economic benefit in Figure 105.

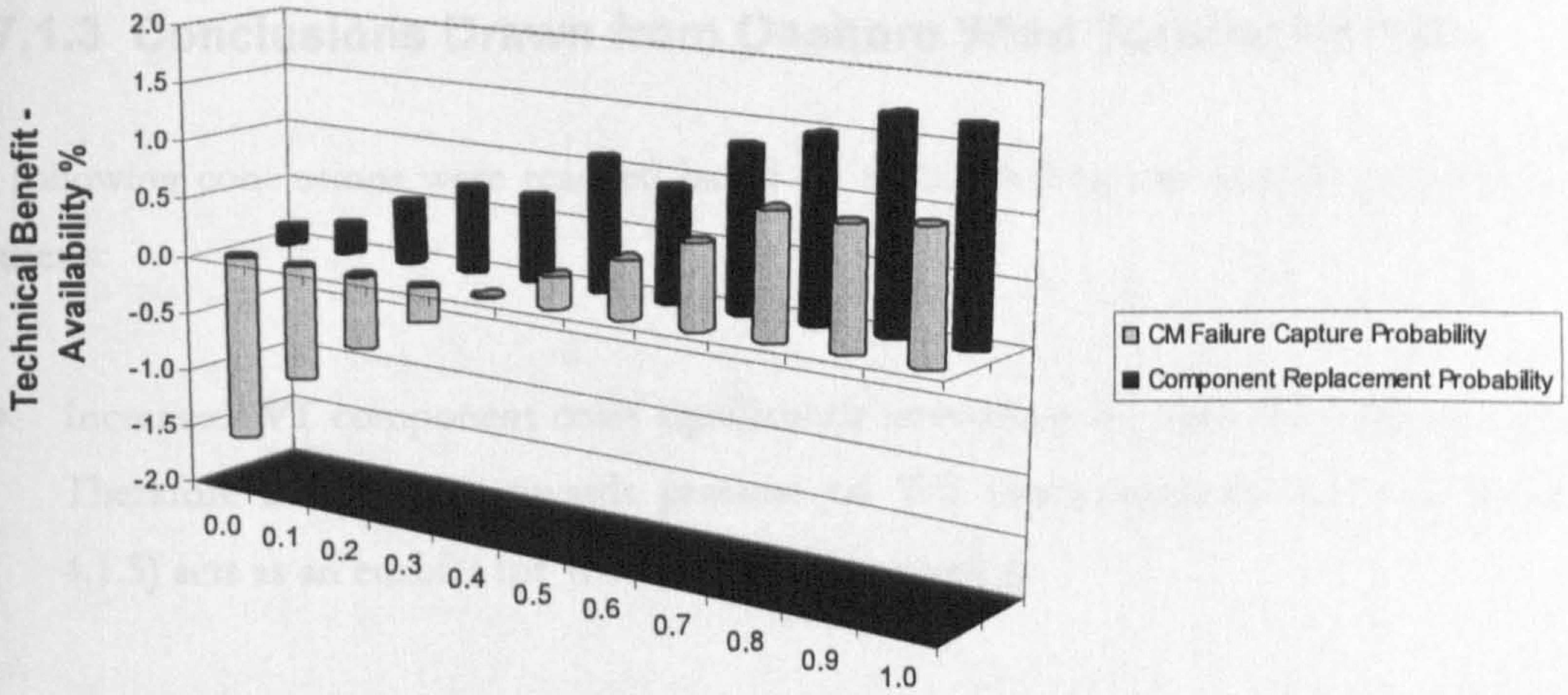

Figure 107: Impact of CM Capability & Reparability on Technical CBM Benefit – Availability Onshore

The perception of the potential benefits of WT CBM in the published literature is that the technical and economic benefits are well aligned, since one flows from the other (e.g. see Hameed et al. 2006). The results presented in this thesis have made explicit linkages between the technical and economic aspects of the wind turbines and the condition monitoring system.

The results can help shape wind farm maintenance policy since the adopted modelling approach has captured diverse operating conditions, and in doing so, provides a robust framework for evaluation of WT CBM benefit.

7.1.3 Conclusions Drawn from Onshore Wind Turbine Results

The following conclusions were reached based on the modelling and analysis presented in this thesis:

- Increased WT component costs significantly strengthen the case for onshore CBM. Therefore the current upwards pressure on WT subcomponent cost (see section 4.1.3) acts as an enabler for WT condition monitoring.

- For onshore sites with modest wind resource (mean~6.95m/s), a high level of component reliability (i.e. $\lambda < 1$) enables CBM because of the resultant decreased maintenance frequency. As reliability decreases, CBM benefit increases as there is more scope for increased maintenance efficiency and CBM costs are not prohibitive. In all base cases CBM is clearly more cost-effective than TBM – *if* CM system diagnosis is 100% and the CM system creates no false positives.

- Economic justification of CBM also hinges on reparability of WT components after failure – if 90% or more of outright failures (requiring reactive maintenance) are fairly minor component repairs requiring relatively modest capital outlay, TBM is more cost-effective than CBM. Caution should be used interpreting this result due to a lack of reliable data on reparability of WT components and costs of repair (as opposed to replacement).

- Onshore CBM benefit is highly dependant on cost of individual WT maintenance actions – labour and equipment costs. Doubling of equipment hire costs and increasing labour rates by 50% (C_{EQ} ,C_{LAB}) acts to reduce CBM benefit as WT reliability decreases (reversing the base case trend).

- If downtime for WT component failures is reduced, CBM benefit also reduces for the case of high and medium WT reliability. However, at a low level of WT reliability, the CBM benefit increases. This is due to a 'secondary' effect of low downtime (i.e. not related to lost energy). WT Availability is boosted because of the low WT failure downtimes, which results in higher component failure rates, because the system is 'exposed' to failure for longer time periods. Intuitively, a reduction in WT downtime would reduce the benefit of CM, because the consequences of an outage are lower and hence the benefit of avoiding those outages is reduced. However, this secondary effect on WT reliability means that the outcome is less straightforward than at first glance.

- CBM benefit associated with increased average wind speed exhibits similar behaviour to the base case: that is WT CBM benefit increasing as WT component reliability decreases. The 'lost energy' cost component becomes more significant than incurred WT maintenance costs as the system as a whole becomes less reliable, driving up CBM benefit. The low reliability WT system coupled with increased average wind speed increases CBM benefit compared to the base case. A major conclusion is that lost energy contribution to WT CBM benefit dominates at high wind sites onshore, but only if component reliability is relatively low.

- WT CM system technical capability was appraised. The WT CM system has to detect 30-40% (or more) of all incipient WT component failures to be economically justified onshore (i.e. detecting the change from the Markov chain from 'fully up' state to a 'derated' state). Whether or not current wind turbine condition monitoring systems can attain this level of fault diagnosis accuracy is open to debate. Alternatively, the system can withstand up to 3 CM-induced false positives per annum and still be more cost-effective than TBM.

7.1.4 Prerequisite 'Conditions for Success' for Onshore WT CM

Taking stock of the onshore results, the key conditions to enable CBM for onshore WTs are defined in Table 52. Looking at these five conditions for success, three are related to the modelling of WT components – reliability and downtime (#1, 2, 3). The main factor impacting on this sub-set of key enablers is how maintenance is modelled. For example, it has been assumed that CBM actions always restore the system to its fully up state. Although this is quite a substantial assumption, the same assumption has been made for TBM.

Similarly, modelling of component repair incurred during maintenance as a factor (α) of the capital cost is a simplistic, but necessary, assumption – again this is the case for both CBM and TBM. If these caveats regarding the modelling are accepted, the key enablers displayed in Table 52 can be considered robust indicators for the economic success of onshore CBM.

#	Condition For Success – Onshore Wind Turbine Condition Monitoring
1	Very strong site wind profile in tandem with low reliability
2	High WT reliability in tandem with high maintenance costs
3	High downtimes for unplanned outage ('tens' of days) – e.g. no easily accessible spares
4	Good technical performance of CMS (40%+ good classification of incipient fault)
5	20%+ of outright failures requiring replacement rather than repair

Table 52: Key Enablers for Onshore WT Condition Based Maintenance

7.2 Offshore Wind Turbine Results

7.2.1 Economic Impacts of Model Input Assumptions

The economic case for CBM applied to offshore wind turbines is summarised in Figure 108 and Figure 109. The broad conclusions in Figure 108 (i.e. assuming perfect CM system) are somewhat dissimilar to those in the onshore case, with CBM benefit reducing as reliability reduces, in contrast with the general onshore trend. Also, the magnitude of the CBM benefit generally increases by orders of magnitude. The low reliability scenario always results in a reduction in CBM benefit, regardless of the other variables.

The main inference from Figure 108 is that the increased downtime and increased mean wind speeds are two key factors which enable cost-effective offshore CBM. Figure 108 also shows that the combination of high WT maintenance costs in tandem with low WT reliability results in a very low economic CBM benefit.

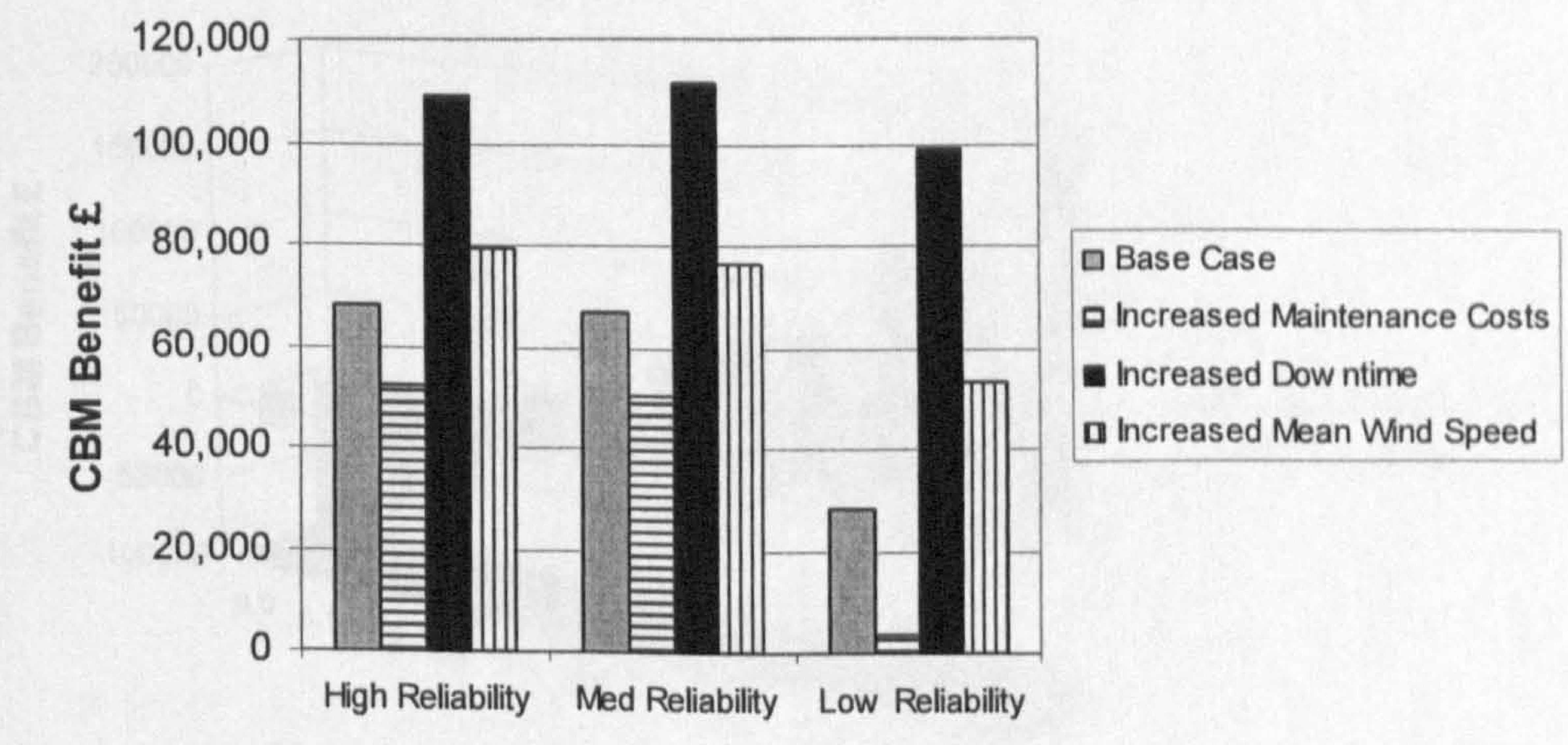

Figure 108: Impact of Model Parameters on Economic CBM Benefit – Offshore

Figure 109 illustrates that the technical performance of the CM system itself (failure capture probability) has a strong bearing on the potential economic benefit for offshore WT CBM. It is noted, however, that the threshold at which CBM becomes economically favourable has reduced compared with the onshore case (see Figure 105). This reflects the potential cost savings for offshore WT CBM, as these are much higher than the onshore case. Even tapping into a fraction of this potential (i.e. detection of 20% of incipient failures before they occur) results in significant economic savings compared to annual TBM.

The impact of WT 'component reparability' in the offshore environment is also a very influential factor in the economic case for offshore WT CBM. Since component costs are significantly higher for a 5MW WT, it is not surprising to see this variable gaining in significance. More repairable WT components render CBM uneconomic, whereas the potential for cost savings is huge if very few repairs can be performed after a failure. If the assumptions provided by Ribrant and Bertling (2007) regarding gearbox replacement probability of 0.6 can be applied to all offshore WT components, CBM has a clear economic case.

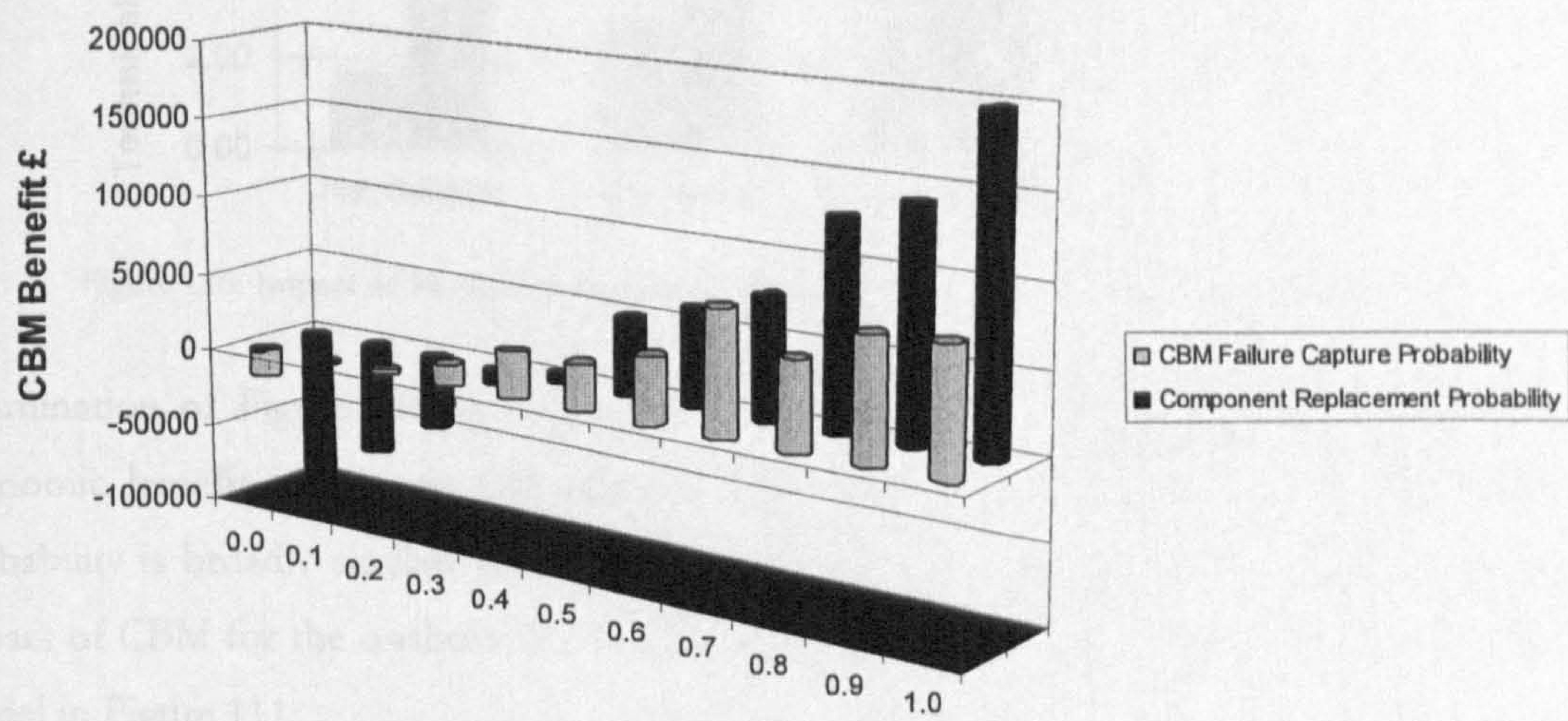

Figure 109: Impact of CM Capability & Reparability on Economic CBM Benefit – Onshore

7.2.2 Technical Impacts of Model Input Assumptions

Figure 110 and Figure 111 summarise the technical impact of CBM in terms of availability for offshore WTs. Figure 110 shows how the increased WT downtime scenario multiplies the technical benefit by a factor of ~3 relative to the base case. This effect is well correlated with the economic impact of increased WT downtime (see Figure 108).

Compared to the onshore WT results (Figure 106), the technical benefit of adoption of CBM for offshore WTs is much higher. In the case of low WT reliability in tandem with increased downtime, the benefit is over 10% in availability improvement.

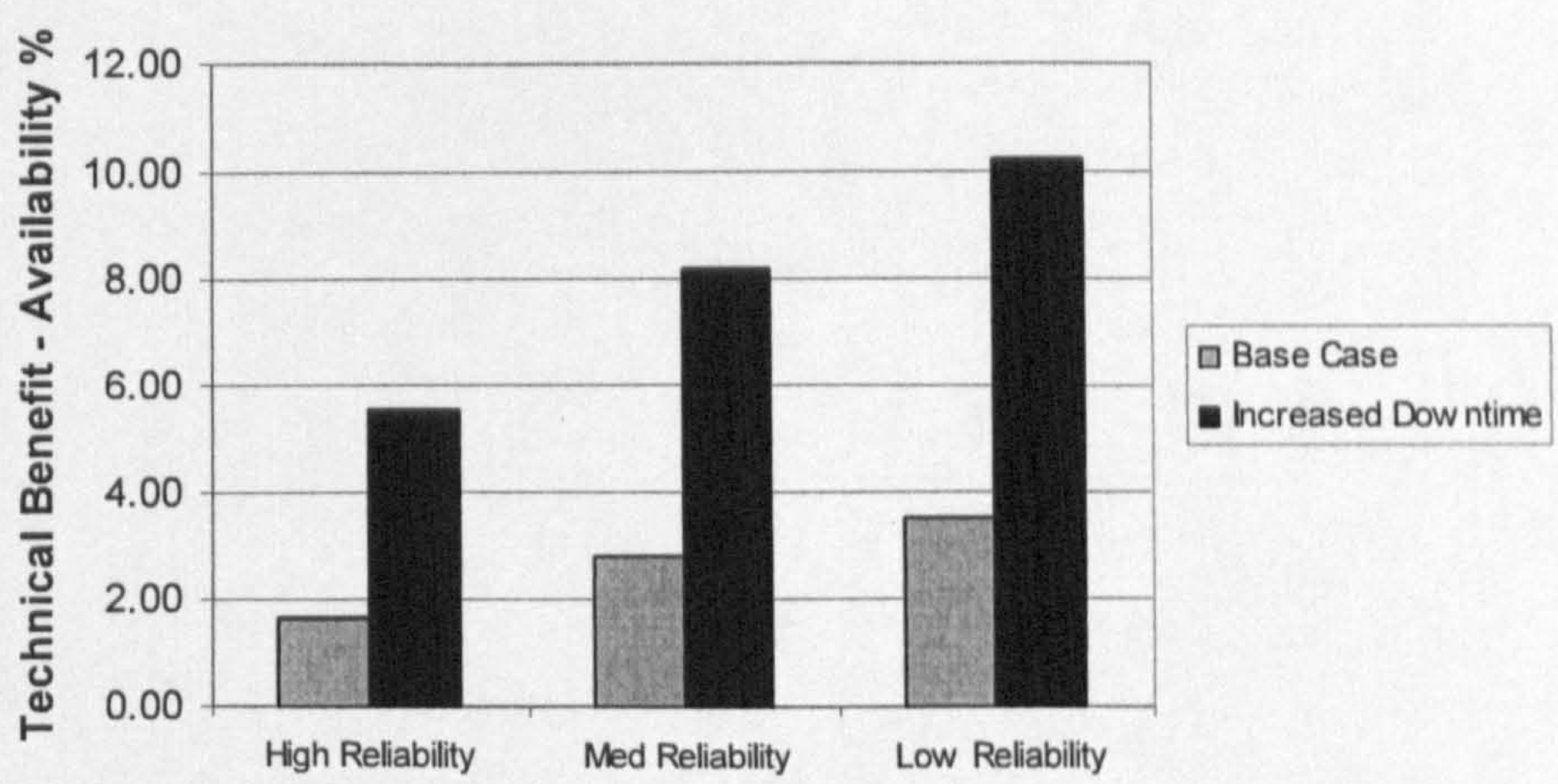

Figure 110: Impact of Model Parameters on Technical CBM Benefit – Availability Offshore

Examination of Figure 111 in comparison with Figure 109 shows that the technical and economic benefit relative to CM failure capture probability and component replacement probability is broadly similar. It is interesting to note that the range of values for technical impact of CBM for the onshore WT model in Figure 107 is very similar to the offshore WT model in Figure 111.

Despite the technical similarities, the economic impact of the offshore and onshore scenarios is very different (as observed by comparing Figure 109 with Figure 105).

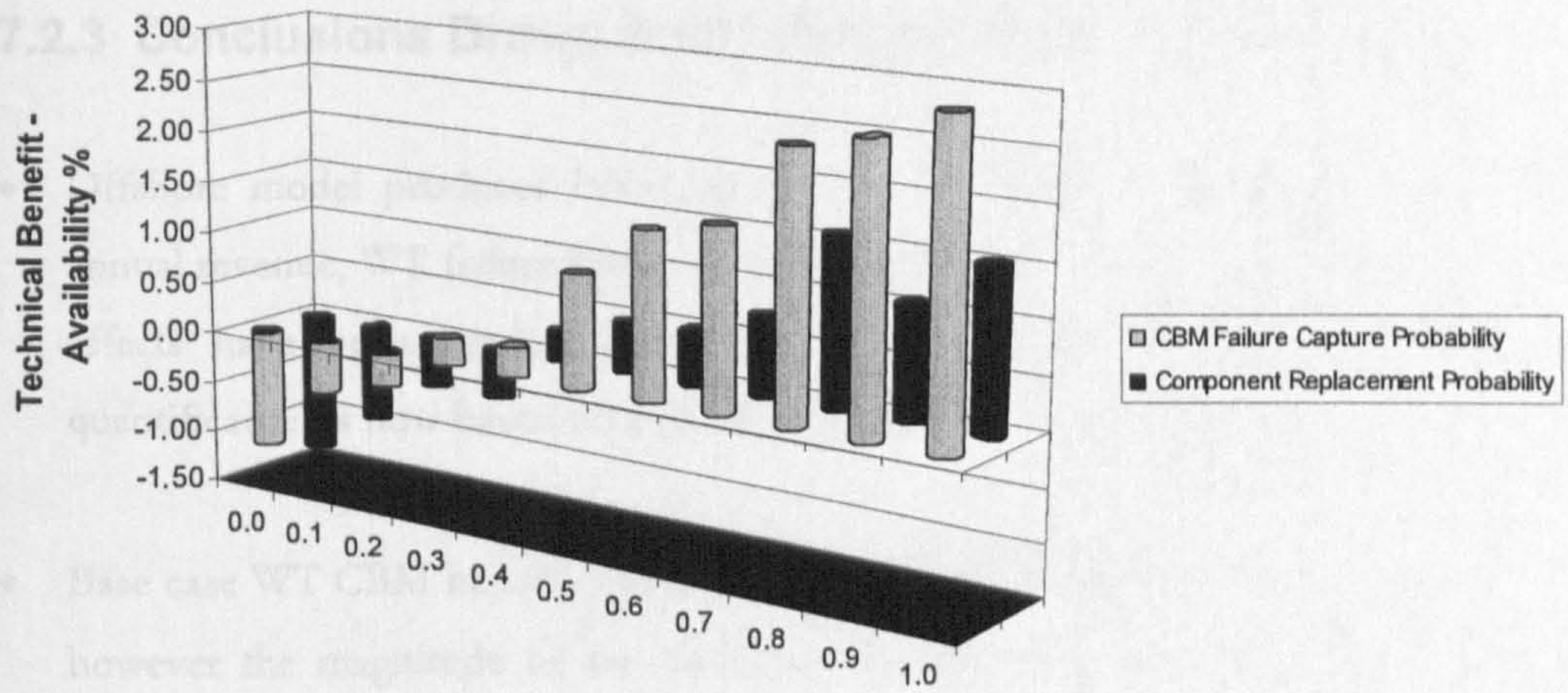

Figure 111: Impact of CM Capability & Reparability on Technical CBM Benefit – Availability Offshore

7.2.3 Conclusions Drawn from Offshore Wind Turbine Results

- Offshore model produces lower overall WT availability but higher energy yields, annual revenue, WT failure rates and lost energy than the onshore WT model. These effects have been predicted and observed by many commentators, but their quantification is now based on solid theoretical and practical foundations.

- Base case WT CBM benefit appears to be significantly larger (x2) for offshore WTs, however the magnitude of the calculated confidence limits makes the size of the benefit unclear.

- Increased WT component costs increase CBM benefit by ~4 times. This compares with a ~2 times increase for onshore conditions. It is concluded that the higher cost of WT component replacements and repairs for offshore WTs is a major enabler for offshore WT CM.

- CBM benefit is strongly coupled with high and low WT reliability scenarios for offshore conditions. The medium reliability has little effect and often generates similar effects to the high WT reliability level (Figure 108). This is because the CBMDM model has been specified based on a system with medium WT reliability level. This shows that the results are also dependent on how the model parameters, such as CBM wait time, are specified.

- Results for reparability of WT components show that the offshore CBM benefit is more sensitive to the ease of WT repair than onshore. If only 30% or less of WT failures have to be replaced rather than repaired, TBM is more cost-effective for offshore WTs than CBM.

- Doubling WT maintenance action costs (specifically, crane hire mobilisation costs) has considerable effect on CBM benefit. CBM benefit across all WT reliability levels is reduced, and CBM benefit is marginal for the low WT reliability, high maintenance cost scenario.

- Downtime increase has large impact on results, clearly tipping the balance in favour of CBM. It has been shown that the 'lost energy' component of CBM benefit is driving this impact. Thus, high WT downtimes for unplanned outages offshore make a persuasive case in favour of CBM, particularly for WTs with low reliability.

- Increase in the mean wind speed (mean=7.95m/s instead of 6.95m/s) boosts the case for CBM over all WT reliability levels. However, it is not as influential as the WT downtime increase previously mentioned.

- The threshold for positive WT CBM economic value in terms of technical capability of the CM system (false -ves) decreases from ~30/40% (onshore) to ~10/20% (offshore). Onshore systems require higher levels of CM technical performance in order to justify themselves economically. Relatively error-prone CMS can still be more cost-optimal than TBM in the offshore environment, because the potential cost savings are very significant. Surprisingly, the result as regards false positive threshold at which CBM becomes uneconomic is similar in onshore (3 false positives per annum) and offshore (4 per annum) conditions.

7.2.4 Conditions for Success for Offshore WT CM

The impact of offshore conditions on the case for CBM is summarised in Table 53, which is an extended version of the equivalent onshore table. One of the key questions posed in the introduction of this thesis was: do offshore conditions present a clear case for CBM?

Broadly speaking, the magnitudes of CBM techno-economic benefit measured from the simulations were much larger in magnitude than the onshore equivalent. Table 53 shows that the drivers are broadly similar and do not change much for offshore conditions. Perhaps the most surprising of the modifications are the reduced requirement on the robustness of the CM system (i.e. lower failure detection probability).

This shows that the potential benefits offshore are indeed much bigger than onshore, and the more reliable the CMS is, the more of this potential techno-economic benefit can be unlocked.

#	Condition For Success – Onshore Case	Offshore Condition for Success Modification/ Comment
1	Very strong site wind profile in tandem with low reliability	Key enabler for both cases
2	High WT reliability in tandem with high maintenance costs	High reliability – key enabler. High maintenance costs – reduces offshore CBM benefit.
3	High downtimes for unplanned outage ('tens' of days) – e.g. no easily accessible spares	Key enabler for both cases
4	Good technical performance of CMS (40%+ good classification of incipient fault)	Less dominant than onshore: threshold for positive CBM benefit is reduced to ~20%
5	20%+ of outright failures requiring replacement rather than repair	More dominant than onshore: threshold for cost effective TBM is raised to ~30% replacements

Table 53: Key Enablers for Onshore WT Condition Based Maintenance - Offshore Modifications

7.3 Appraisal of Results

The results presented in this chapter have demonstrated the main innovation of this thesis – that is to quantify the benefits of adopting condition based maintenance for wind turbines taking into account key factors such as WT operating conditions as well as robustness and accuracy of the CM system itself. In the existing literature on this subject, these issues are often glossed over and their impact is often not quantified which is detrimental to the model accuracy.

The key value of this work is that it provides a quantitative evaluation of the techno-economic merits of wind farm maintenance policies which have not been provided until now. Maintenance policy decisions are currently based either on manufacturers' recommendations or assumptions that wind turbines should be maintained in a way similar to other power systems utility assets such as circuit breakers (i.e. TBM). The proposed method can provide decision support for wind farm maintenance policy decision makers (operators, utilities, O&M sub-contractors): information and insight which has not been available until now.

The analysis contained in this thesis shows that TBM applied to wind turbines may not be cost optimal or provide the highest technical benefit. However it also shows that certain conditions are prerequisites for the techno-economic benefits of CBM to be realised. Some of these conditions are surprising – for example the analyses show that the case for CBM is marginal in the case of offshore WTs with a low level of reliability, coupled with high maintenance costs. Compared to the TBM policy, which is restricted to one maintenance action per annum, the CBM policy will incur more maintenance actions because of the high number of incipient failures, and the increased cost of these actions decimates the economic benefits of CBM in this case. This is a credible scenario given the hostile conditions offshore, which may act to reduce WT reliability. This conclusion is not one which has been reached in the existing literature: however it demonstrates the value of the approach proposed in this thesis.

Similarly, the results have shown that the diagnosis accuracy of the CM system has to be higher onshore to justify a cost-effective CM system. This reflects the fact that the *potential* savings achieved by adoption of WT CBM are larger offshore. It also provides a benchmark in terms of successful fault classification, which CM systems should be able to meet in order that the CM system is economically justified.

In terms of the approach taken to the modelling, the Markov chain solved via MCS has been demonstrated as a suitable model framework to capture the nuances of wind farm operational issues, some of which are neglected by other studies because other frameworks cannot handle issues such as modelling of the CM system. As well as being flexible and accurate, another advantage of the method is the small number of parameters, which can be estimated from limited data. This is important, since the experience during this research was that this kind of operational data is sparse or non-existent. Another advantage of the methodology is that it is not necessarily retrospective – reliability, downtime, costs etc. will be known from other wind farm sites or can be estimated from existing bodies of data such as windstats.

It is conceded that the approach proposed in this thesis has some limitations. The most obvious of these is that if many intermediate states are modelled, the state space would quickly become unwieldy and difficult to visualise. For example, if four states were used to characterise the deterioration of gearbox, generator and rotor blade instead of three states (as has been assumed in this thesis), and two states as before for E&E failures, then the equivalent number of states would be:

$$4^3 \times 2 = 128$$

Simplifying assumptions could be used to cut this number down (earlier in the thesis this reduced the number of states by around 50% - see section 4.1.6). However, this still results in around 60 states. Similar problems are encountered if more components are to be included in the model. The inclusion of one extra three state component in the model presented in this thesis would mean the number of states increasing to:

$$3^4 \times 2 = 162$$

It can be observed that this approach suffers from the so-called 'combinatorial explosion' problem which is an issue for many approaches which use the concept of a discrete state-space. The counter-argument to this problem questions how many states are actually required to characterise deterioration of WT components. This, in fact, is a fundamental question in deterioration modelling.

The answer depends on the application of interest. For example, if the objective of the work is to gain a deep understanding of the mechanics of deterioration behaviour, then a higher number of states would probably be necessary to capture various stages of the deterioration characteristic. An example of this would be a bearing fault: this might start with an extreme weather event causing excess vibration, damaging a rolling element. The damaged element could wear away the bearing race over a period of days or weeks, slowly causing eccentricity and then misalignment on the rotor shaft. Finally this misalignment might cause a rotor shaft to snap or a serious problem inside the gearbox. Modelling of the intricacies of the deterioration process using a Markov chain would probably necessitate many more states than the three state representation used in this thesis, because the process stages (as hypothesised above) would be modelled in high detail. Conversely, if the modeller is simply concerned with typical probabilities (or times to failure), but also wants to capture basic deterioration behaviour, three states (as used in this thesis) may be adequate.

The key strength of this work is that it has enabled the key drivers for implementation of a condition based maintenance system for wind turbines to be identified (See Table 53). Furthermore, the magnitude of the benefit under various conditions has been calculated. These outcomes have been derived on the basis of sound quantitative, probabilistic analysis tools as described in this thesis.

7.4 Future Work

The work presented in this thesis could be built on in the future to investigate other specific issues of interest.

One interesting concept is the idea of benchmarking the operational performance of different WT concepts and maintenance policies. For example, a new multi-generator design is being developed by a WT manufacturer, the idea being that the increased redundancy could let the WT run even if one or two generators fail – much like aircraft engine redundancy. It would be very interesting to compare the reliability of different WT configurations alongside the impact of maintenance policies. For example, applying an extended CM suite to a conventional Danish concept WT (could be modelled by assuming a high CM capture probability) and comparing technical and economic aspects to multi-generator design with TBM applied. The multi-generator WT could be modelled via a conventional reliability block diagram coupled with MCS. Similar analyses could be conducted for direct drive machines, multi-rotor machines or VAWTs. No analysis of this type has ever been published but it would be possible to achieve by making minor modifications to the models underpinning this thesis.

The primary focus of this thesis has been the ongoing costs of wind farm operation. Capital costs of the condition monitoring equipment have not been considered, since CM systems including temperature and vibration monitoring are now included at manufacture as standard in MW-class turbines (rather than an optional extra). The key question addressed in this thesis has therefore been whether or not the CM information will be utilised as part of the operational strategy, or simply ignored in favour of TBM. Nevertheless, new CM methods are continually being developed, some of which may involve extra capital outlay. One area of future work of interest is to appraise the added value of novel, individual CM solutions taking into account the capital cost needed for deployment. For example, acoustic sensors have been suggested as a novel method for monitoring the deterioration of WT rotor blades. If the incipient fault diagnosis accuracy (e.g. false negatives and false positives) of an acoustic-based blade monitoring system could be quantified, and the capital costs were known, then the incremental value of such a system could be evaluated using the techniques presented in this thesis.

Another possible avenue for future research, building on this thesis, is the use of the models to evaluate the financial viability of wind farms for future economic scenarios. For example, it is unknown whether or not that the ROC subsidy mechanism for renewable electricity will be supported beyond 2021 (the current lifetime of the ROC system). The model parameters could be altered to establish if wind farms could remain economically viable in a future low-subsidy environment. Since utilities are interested in staying one step ahead in terms of future revenue projections and impacts, the models in this thesis could be modified for this purpose, and would be of interest. Investor confidence is always an issue in large infrastructure projects and the models produced in this thesis could reduce uncertainty by predicting the economic viability of future wind farm projects.

Appendix A – Solution of Simplified 3-State Markov Process

Derivation of time dependent probabilities, reliability and MTTF of three state system with state three set as an absorbing state (necessary for calculating MTTF).

$$P_1(t+\delta t) = (1-\lambda\delta t)\, P_1(t) \qquad (1)$$

$$P_2(t+\delta t) = (1-\lambda\delta t)\, P_2(t) + \lambda\, P_1\delta t \qquad (2)$$

$$P_3(t+\delta t) = P_2(t)\,\lambda\delta t + P_3(t)\,(1) \qquad (3)$$

Rearranging equations 1, 2 and 3 yields:

$$\frac{P_1(t+\delta t) - P_1(t)}{\delta t} = -\lambda\, P_1 \qquad (1)$$

$$\frac{P_2(t+\delta t) - P_2(t)}{\delta t} = -\lambda\, P_2 + \lambda\, P_1 \qquad (2)$$

$$\frac{P_3(t+\delta t) - P_3(t)}{\delta t} = \lambda\, P_2 \qquad (3)$$

If δt becomes sufficiently small then this linear approximation of the function can be expressed as a differential. The three resulting differential equations are best summarised in matrix form:

$$\begin{bmatrix} P'_1(t) & P'_2(t) & P'_3(t) \end{bmatrix} = \begin{bmatrix} -\lambda & \lambda & - \\ - & -\lambda & \lambda \\ - & - & - \end{bmatrix} \times \begin{bmatrix} P_1(t) & P_2(t) & P_3(t) \end{bmatrix}$$

In order to solve more easily, firstly transform into the s-domain:

$$sP_1(s) - P_1(0) = -\lambda P_1(s) \qquad (1)$$

$$sP_2(s) - P_2(0) = +\lambda P_1(s) - \lambda P_2(s) \qquad (2)$$

$$sP_3(s) - P_3(0) = +\lambda P_2(s) \qquad (3)$$

Assuming the initial conditions at time t=0 are $P_1(0)=1$, $P_2(0)=0$ and $P_3(0)=0$, then:

$$\therefore\ sP_1(s) - 1 = -\lambda P_1(s) \text{ and } (s+\lambda)\, P_1(s) = 1 \qquad (1)$$

Similarly: $sP_2(s) + \lambda P_2(s) = \lambda P_1(s)$ and $(s+\lambda)\, P_2(s) = \lambda P_1(s)$ (2)

And $sP_3(s) = \lambda P_2(s)$ (3)

Rearranging the above expressions yields:

$$P_1(s) = \frac{1}{(s+\lambda)} \qquad (1)$$

$$P_2(s) = \frac{\lambda}{(s+\lambda)} P_1(s) \qquad (2)$$

$$P_3(s) = \frac{\lambda}{s} P_2(s) \qquad (3)$$

Substitute (1) into (2): $P_2(s) = \dfrac{\lambda}{(s+\lambda)} \cdot \dfrac{1}{(s+\lambda)}$ or $P_2(s) = \dfrac{\lambda}{(s+\lambda)^2}$

Convert expressions for P_1 and P_2 from s-domain back to time domain using Laplace transforms:

$$P_1(t) = e^{-\lambda t} \quad (1)$$

$$P_2(t) = \left[\frac{1}{(2-1)!} \cdot t^{2-1} \cdot e^{-\lambda t}\right] \cdot \lambda \qquad \text{or} \qquad P_2(t) = \lambda\, t\, e^{-\lambda t} \qquad (2)$$

To form an expression for reliability, the time dependent probabilities for the functional states are summed. This is the final analytic formulation of the reliability –

$$\therefore\ R(t) = P_1(t) + P_2(t) = e^{-\lambda t} + \lambda\, t\, e^{-\lambda t} = (1+\lambda t)\, e^{-\lambda t}$$

The mean time to failure is obtained by integrating the expression for reliability:

$$MTTF = \int_0^{\infty} R(t)\, \delta t$$

$$\therefore\ MTTF = \left[-\frac{1}{\lambda}e^{-\lambda t} + \lambda \frac{e^{-\lambda t}}{\lambda^2}(-\lambda t - 1)\right]_0^{\infty} = \left[-\frac{1}{\lambda}e^{-\lambda t} - t\, e^{-\lambda t} - \frac{1}{\lambda}e^{-\lambda t}\right]_0^{\infty}$$

$$MTTF = \left[-\frac{2}{\lambda}e^{-\lambda t} - t\, e^{-\lambda t}\right]_0^{\infty} = [0]^{\infty} - \left[-\frac{2}{\lambda}\right]^{0} \qquad \therefore \qquad MTTF = \frac{2}{\lambda}$$

The expression for availability is shown below, based on the analytic calculations. If $\lambda=1$ per annum and MTTR=1/12 (1 month) the availability can be quantified.

$$Availability = \frac{MTTF}{\mathrm{MTTF} + \mathrm{MTTR}} = \frac{2}{2+0.08333} = 96\%$$

Appendix B – Understanding the Student-t Probability Density Function

Student-t distribution probability density function (pdf) is characterised by Equation 1, where v is the number of degrees of freedom and t is the random variable.

$$f(v,t)=\frac{\Gamma\left(\frac{v+1}{2}\right)}{\sqrt{v\pi}\,\Gamma\left(\frac{v}{2}\right)}\cdot\left(\frac{t^2}{v}+1\right)^{-\left[\frac{(v+1)}{2}\right]}$$

Equation 1

In the example considered in this thesis, v=29. Therefore according to Equation 1, the Gamma function (Γ) has to be evaluated at 15 and 14.5 – Γ(15) & Γ(14+1/2). For positive integer values of v, the gamma function can be approximated by the factorial in Equation 2.

$$\Gamma(v)=(v-1)!$$

Equation 2

Therefore, for this example Γ(15)=(15-1)!=87178291200 – this is the numerator of the first term of Equation 1. Finding the gamma function for half-integers (e.g. 14.5 – denominator) is more complex. Equation 3 illustrates an identity which can be used to calculate half-integers of the Gamma function.

$$\Gamma\left(v+\frac{1}{2}\right)=\sqrt{\pi}\,\frac{(2v-1)!!}{2^v}$$

Equation 3

$$(2v-1)!!=\frac{(2v)!}{2^v v!}$$

Equation 4

The double factorial term – (2v-1)!! – can be simplified into the expression in Equation 4. Since v + ½ from Equation 3 is equivalent to 14 + 0.5, the double factorial resolves to 28! i.e. 3.04888 x 10^{29} is the numerator of Equation 3. The denominator is simply 2^v=2^{14}=16384. Equation 3 becomes:

$$\Gamma\left(v+\frac{1}{2}\right)=\sqrt{\pi}\,\frac{(2v-1)!!}{2^v}=\sqrt{\pi}\,\frac{3.0488\,x10^{29}}{16384}=23092317922$$

The first term of the student-t pdf (Equation 1) can therefore be calculated:

$$\frac{\Gamma\left(\frac{29+1}{2}\right)}{\sqrt{29\pi}\,\Gamma\left(\frac{29}{2}\right)}=\frac{87178291200}{2.20415\text{x}10^{11}}=0.395518579$$

This first factor, calculated above, has the effect of scaling the second term (re-stated below) of the student-t pdf, which is plotted in Figure 112. This clearly shows the nature of the student-t distribution, which is utilised in the thesis to estimate confidence limits.

$$\left(\frac{t^2}{v}+1\right)^{-\left[\frac{(v+1)}{2}\right]}$$

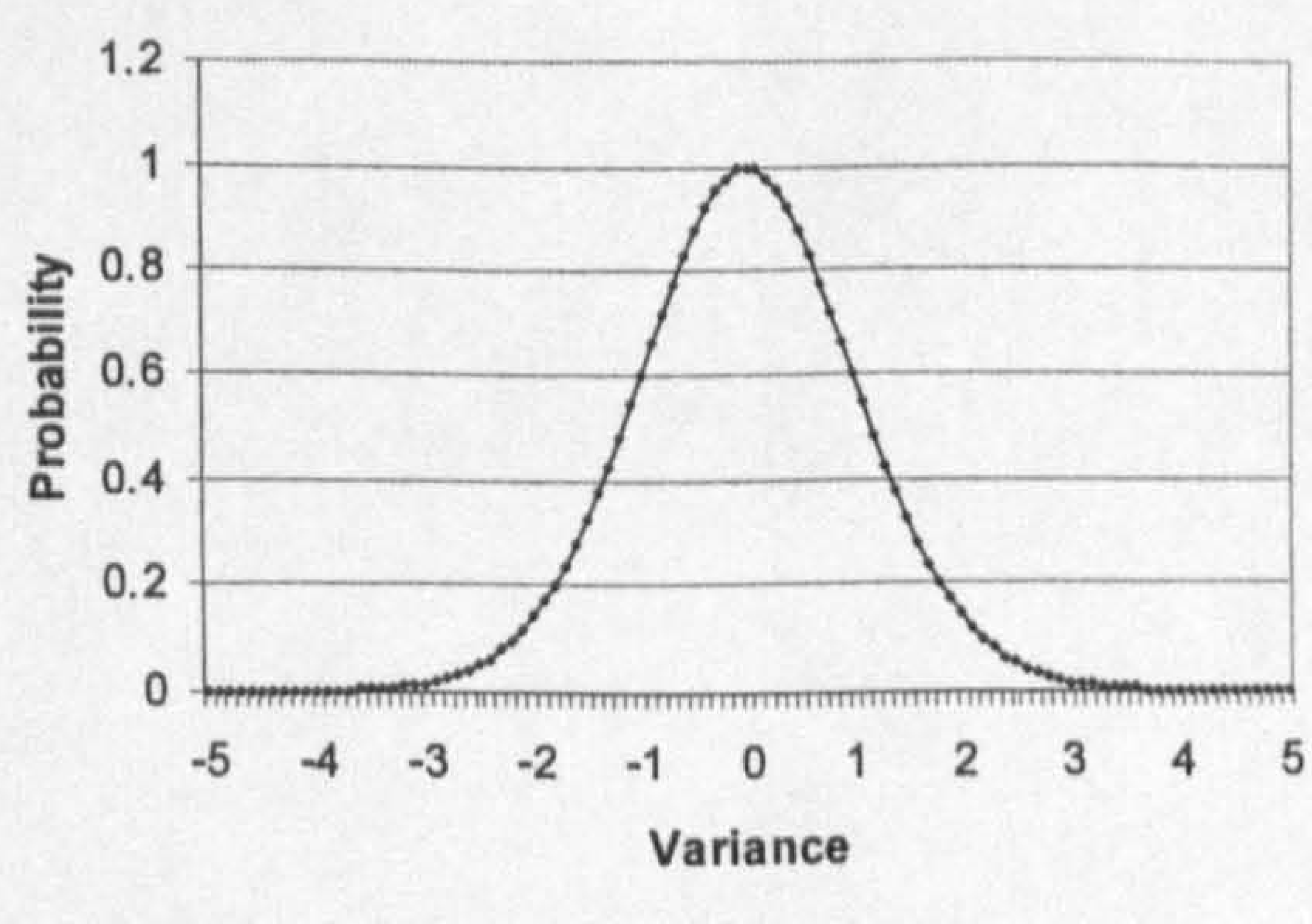

Figure 112: Second Term of Student-t PDF for 29 Degrees of Freedom

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