A REAL OPTIONS OPTIMIZATION MODEL TO MEET AVAILABILITY REQUIREMENTS FOR OFFSHORE WIND TURBINES

Gilbert Haddad, Peter Sandborn, and Michael Pecht
Center for Advanced Life Cycle Engineering (CALCE)
1103 Engineering Lab Building
Department of Mechanical Engineering
University of Maryland
College Park, MD 20742
Telephone: (301) 405-5323
ghaddad@calce.umd.edu

Abstract: This paper provides an optimization model based on Real Options (RO) and stochastic dynamic programming for the availability maximization of an offshore wind farm with prognostic capabilities. Alternative energy sources such as offshore wind turbines are promising technologies, but they are capital intensive projects, and the economics of the project depend heavily on the wind resources, and the availability of the turbines. Prognostics and health management (PHM) is an enabling technology that potentially allows for reduced life cycle cost through a transition from cycle or time based to demand-based maintenance, performance based logistics, and condition-based maintenance. This is especially important for offshore wind farms that require non-traditional resources for maintenance, and are often located in sites that are not always accessible. The proposed model uses information from the PHM system in order to allocate appropriate investments in maintenance while maintaining a specified availability requirement. The RO theory provides promising means to address the economic aspects of PHM after prognostic indication, and assessing the cost required for meeting availability requirements.

Key words: Maintenance optimization, Real options; Post-prognostic indication, PHM, CBM; Availability, Wind Turbines

Introduction: Wind energy has become an attractive source of energy because it is free, abundant, and is perceived as having a low impact on the environment. To make a case for wind energy, the United States Department of Energy (DoE) and the National Renewable Energy Lab (NREL), under the ‘20% Wind Energy by 2030’ plan, announced that the US could feasibly increase the wind energy’s contribution to 20% of the total electricity consumption by 2030 [1]. Given the US dependency on fossil fuels, which are decreasing in supply and increasing in cost, coupled with increasing energy demand, it appears opportunistic to invest in renewable energy sources. Offshore wind has become of subject of interest to the DoE [2] and [3]. The rationale behind this interest is that coastal states, which are home to much of the US population, consume around 75% of the nation’s electricity. Furthermore, offshore wind resources are abundant within reasonable distances from these major urban load centers, which will minimize transmission cost and efficiency [2]. Operation and Maintenance (O&M) accounts for the second largest contributor to the life-cycle cost of offshore wind turbines as can be seen in Figure 1. Hence the importance of decreasing and optimizing O&M has become a major topic of research.

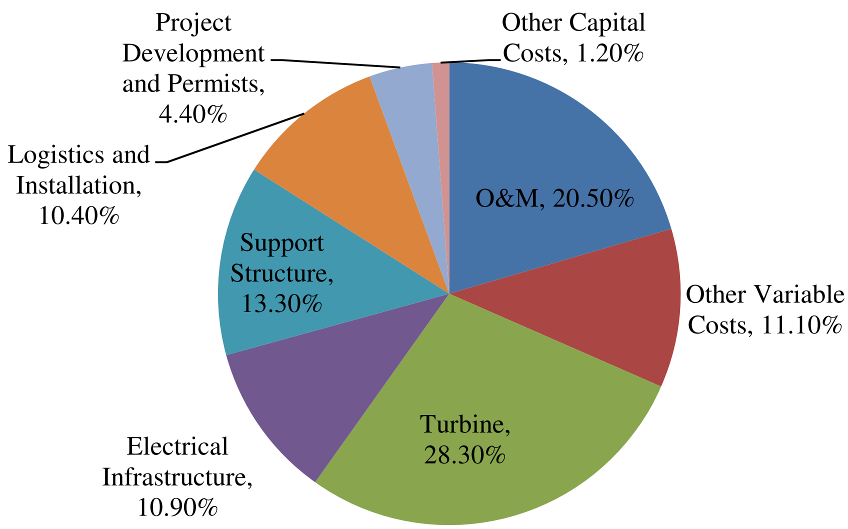

Figure 1: Estimated Life-Cycle Cost Breakdown for a Typical Baseline Offshore Wind Project [2]

Wind farms are capital intensive projects, and the economics of these projects depend heavily on the wind resources, and the availability of the turbines. Availability is the ability of a service or a system to be functional when it is requested for use or operation [4]. Wind farms cannot be depended on for energy generation if they are always down waiting for maintenance. Availability of a system is a function of the system's reliability and how efficiently it can be maintained when it does fail. There are different approaches to maintenance, but fundamentally, depending on if a system has failed, when we think it will fail, how it has failed, etc., there are decisions that need to be made about how to and when to maintain it. Condition monitoring (CM) and prognostics and health management (PHM) have increasingly became of interest to the wind energy community [5]. PHM is a discipline consisting of technologies and methods to assess the reliability of a product in its actual life cycle conditions to determine the advent of failure and mitigate system risk, [6] and [7] . It is a technology that allows complex systems to shift from traditional time or cycle-based maintenance to condition-based maintenance (CBM). It is also an enabler of performance-based contracts and potentially reduces life-cycle cost.

Maintenance of offshore wind farms is challenging as it requires non-traditional resources such as vessels with cranes along with dedicated maintenance crews. Weather conditions may also play an important role; crews cannot perform maintenance if weather conditions are adverse. This work proposes a new method to find optimal maintenance policies for wind farms and contributes to finding the cost/investment needed to maintain a required availability.

This paper is structured as follows: the benefits of PHM are first discussed. The maintenance flexibility that PHM provides is then formally introduced. The mathematical formulation of the optimization model is provided, and an example of a hypothetical wind farm is presented, then the conclusions are discussed.

PHM Enabling New Maintenance Paradigms: PHM has been shown to be beneficial for the health management of systems, and potentially provides a number of benefits (defined as cost avoidance opportunities) including, [6], [4] and [8]:

- Avoiding failures
  - Minimizing the cost of unscheduled maintenance
  - Increasing availability
  - Reducing risk of loss of system
  - Increased human safety
- Minimizing loss of remaining life
  - Minimizing the amount of remaining life thrown away by scheduled maintenance actions
- Logistics (reduction in logistics footprint)
  - Better spares management
  - Optimization of resource usage
- Improved repair
  - Better diagnosis and fault isolation
  - Reduction in collateral damage during repair
- Reduction in redundancy (possible in the long term)
- Reduction in no-fault-founds

PHM has emerged as a key enabler for achieving system reliability/quality, maintainability, testability, safety, and affordability. Hameed et al. [5] provides a review of the PHM methods implemented on wind turbines. These include: vibration analysis for bearings and gearboxes, oil analysis, thermography for failure identification of electronics, physical condition of material, strain measurements for blades, process parameters, and performance monitoring. These methods vary in their degree of maturity - some of them are implemented on a large number of turbines, while others are still in the proof-of-concept stage.

Current maintenance practice for wind farms mainly consists of scheduled maintenance, corrective maintenance (CM), and preventive maintenance, [5] and [9]. Researchers have addressed the optimization of maintenance for wind farms, however the research for offshore wind farms is less abundant and the reason is that PHM is still at early stages in offshore wind farms, and the number of offshore wind farms is still relatively small compared to farms on land. Byon et al. [10] examine optimal repair strategies for wind turbines operated under stochastic weather conditions. Based on the information from in-situ monitoring, the authors derive an optimal preventive maintenance policy that minimizes the expected average cost over an infinite horizon based on a Markov process.

Rademakers et al. [11] describe two simulation models for O&M, and illustrate the features and benefits of their models through a case study of a 100 MW offshore wind farm.

The current work differs from published work in that it provides a new economic basis to value the options that arise to the decision-maker after a prognostic indication. This can lead to a method to quantify the value PHM brings to its user, and a basis to manage the flexibility (e.g., when to perform maintenance after a prognostic indication) enabled by PHM systems using Real Options (RO) theory. Real Options Analysis (ROA) is extended from the class of financial options where the underlying assets are real assets or opportunities for cost avoidance (rather than securities that can be traded) [12]. No research has been performed on RO-based methods to optimize maintenance decisions for offshore wind farms.

CBM has been shown to be an effective way to approach the health management of systems. However, CBM has drawbacks; one of them is illustrated in Figure 2. Suppose a wind farm has 40 turbines with prognostic capabilities (e.g., performance monitoring). If all of the turbines had prognostic indications, each indicating a different remaining useful life (based on accumulated degradation), what is the optimal way to perform maintenance when the maintenance vessel is at the wind farm? For example, which of the turbines circled in Figure 2 should be maintained? What criteria would be used to decide?

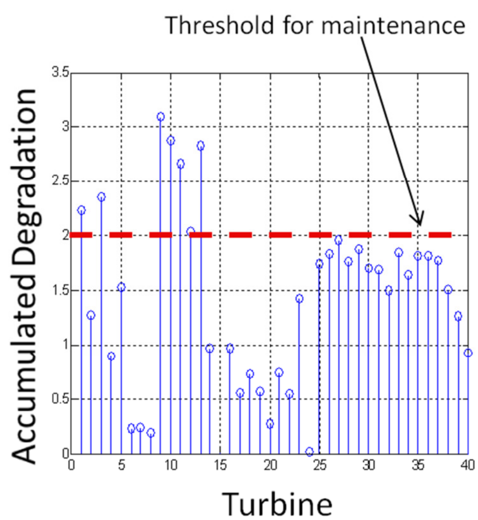

Figure 2: Illustration of Accumulated Degradation on 40 Wind Turbines

The maintenance of wind farms involves the logistics associated with assets needed to perform maintenance and can be costly. If the wind turbines are off shore, for example, sending the maintenance vessel to the wind turbines is an expensive proposition and knowing which of the turbines need to be fixed when the maintenance vessel is on site is important – it may be significantly less expensive to throw away RUL in some wind turbines than to risk having them non-operational or having to make special trips to them for maintenance. Furthermore, a minimum overall availability must also be ensured of the wind farm becomes quickly unviable.

The Flexibility Enabled by PHM: RUL is the remaining useful life that a system has and it effectively represents the lead time (subject to appropriate uncertainties) for the decision-maker or other maintenance entities to take preventive actions prior to a failure. This can be described as a flexibility phenomenon whereby entities involved with the operation, management, and maintenance of a system have the flexibility to take actions within or after the end of the RUL. Hence assessing the value of the using the RUL is of prime importance and gives the decision-maker the true value of cost avoidance when using PHM. Minimizing the amount of remaining useful life thrown away is an example whereby the knowledge about the time of the failure (or time to the failure) allows the decision maker to avoid unscheduled maintenance (where the system is run to failure) and scheduled maintenance (where useful life may be thrown away by changing or removing a part when it still has remaining useful life).

When an anomaly is detected in a PHM-enabled system, and the remaining useful life (RUL) of the system is estimated, the decision maker is then faced with multiple choices called options, which can be exercised or not exercised to manage the health of the system. An 'option' is a right, but not an obligation to take a particular action in the future. Real Options Analysis (ROA) is used to value or assign a monetary equivalent to the maintenance options arising from the implementation of PHM. The quantifications of the options will eventually lead to an optimization problem that identifies the optimal management of the system.

In the wind farm problem, when a prognostic-indication is obtained the decision-maker has the option to turn the turbine off in order to avoid further damage, modify the wind turbine's operation in such a way as to reduce the loading, or continue normal operation (do nothing). Note that there are several uncertainties that tie into the picture and should be accounted for in the ROA analysis. For this purpose, it is essential to draw a distinction between two types of risks for the ROA analysis: market risks and private risks. Risks that can be captured in the value of a traded security are market risks and all others are private risks [13]. As an example the price of power produced by wind turbines may be regarded as market risk because it is contingent on the price of other sources. An example of private risk is the risk associated with the technology and its efficiency. This distinction between the types of risks is important for the valuation process and usually dictates the most appropriate real option valuation method to be used. For projects involving path-dependence (typical for engineering problems) and private risk along with the market risk, methods like simulations and stochastic programming are generally used [14].

Mathematical Formulation: PHM enables the flexibility to shift from cycle-based or schedule-based maintenance to more cost-effective, condition-based maintenance. The latter has its own drawbacks and needs to be optimized. RO is used to optimize which turbines to be maintained each time a maintenance vessel is at the wind farm. Maintaining a turbine can be regarded as an investment under uncertainty. Uncertainty can arise from multiple sources: uncertainty in the prediction of the RUL, uncertainty in the market price for power, and uncertainty in weather conditions. The problem can be formulated to determine the optimal portfolios of real options to purchase [15] and [16] . Optimization of maintenance for these systems provides a significant opportunity for cost reduction. Figure 3 is a decision tree for one turbine. We consider two stages for the formulation. In dynamic-programming terminology, each point where decisions are made is usually called a stage of the decision-making process. Maintenance can be carried out in stage 1, in stage 2, or in both.

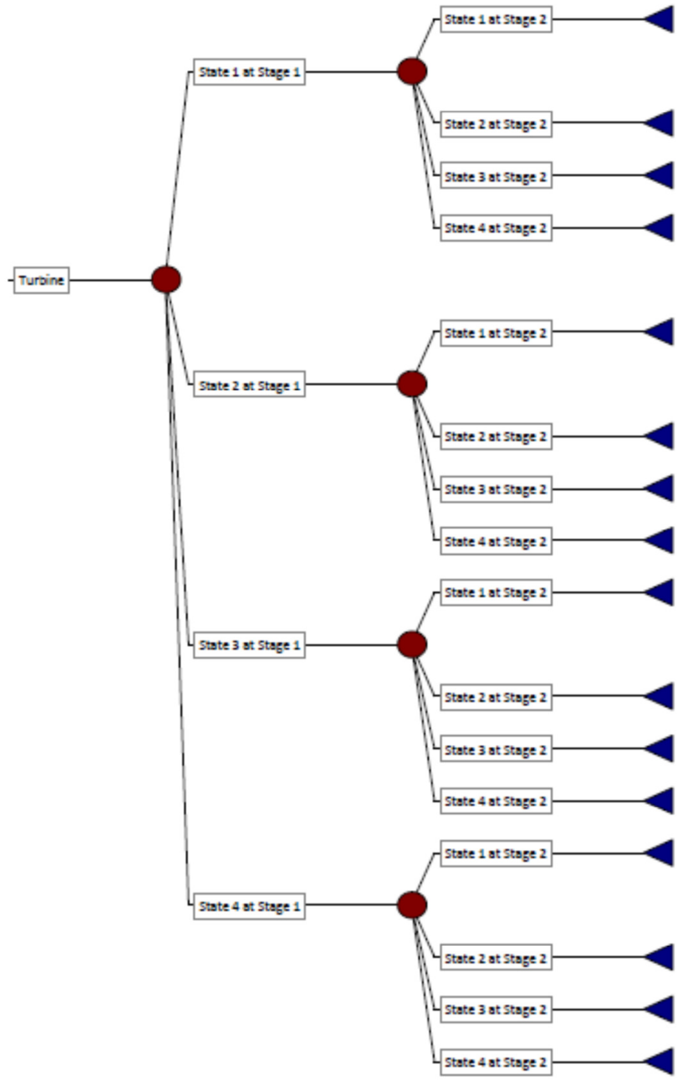

Figure 3: Illustration of a Wind Farm with Four Turbines

The information that summarizes the knowledge required about the problem in order to make the current decisions is called a state of the decision-making process. In the turbine example they represent degradation state. States indicate the health of the turbine at a particular stage. A turbine starts from a healthy state, and degrades with time and operation. The turbine can transition to different states. A state indicates the degradation level of the turbine. The information about the states is obtained from the PHM and condition monitoring system. This is analogous to a 'health index' for the turbine. A probability is associated with the transition between states. The transition probability is associated with the uncertainty in the PHM system; i.e., how accurately it can assess the state of the turbine at each stage.

The implementation of PHM can be considered as the purchase of maintenance options. A sunk cost is invested in PHM, which will provide knowledge about the states of the system in the future, hence enabling condition-based maintenance. This problem can be considered a portfolio optimization problem where the decision-maker has to invest the lowest amount possible in maintenance (to maximize the profit) while satisfying a required availability. The solution to such a problem can be performed by stochastic dynamic programming as outlined below [15].

The set of feasible decisions is given by:

$$X(C_t) = \begin{cases} X_t \epsilon \{0,1\}^I : \sum_{i \epsilon I} \alpha_{it} X_{it} \leq B_t \\ X_{it} = 0 \; if \; C_{it} = \phi \; \vee \; i \epsilon I \end{cases} \tag{1}$$

where,

- C_t = the state of turbine *i* at stage *t*
- X_{it} = the decision variable of whether to invest in maintenance in turbine *i* at stage *t* 0 means do not invest, and 1 means invest
- α_{it} = the cost of maintaining turbine *i* at stage *t*
- B_t = the budget available for stage *t*
- *e* = desired state at the end of stage 2
- V = maintenance decision

Equation (1) says that the investment in maintenance at each level should be less than the budget. If we want to choose an optimal investment strategy to maximize the probability that at least one turbine will be in the healthy state at stage 2, then we solve for {0,1} decisions indicating funding/no-funding decisions using the following stochastic program [15]:

$$V_t(C_t) = min_{X_t \epsilon X(C_t)} \, E\{V_{t+1}(C_{t+1}) | C_t, X_t\} \tag{2}$$

where

$$V_{t+1}(C_{t+1}) = \begin{cases} 1 \; if \; C_{i,t+1} = e \; for \; some \; i \epsilon I \\ 0 \; otherwise \end{cases} \tag{3}$$

Example: We consider a hypothetical wind farm with four turbines to demonstrate the method outlined in equations (1)-(3). The objective is to determine the optimum subset of turbines to be maintained at each stage given a budget constraint that can be spent on maintenance for each stage in monetary units (MU). The goal is to meet an availability requirement that at least one turbine should be in operation after stage 2.

The assumed cost for maintenance for each turbine at each stage is given in Table 1. The table is an input to the model. The cost of performing maintenance is different for each turbine because of the stochastic nature of the degradation of systems, and the specific subsystem to be maintained: the maintenance of a gearbox is more costly than the maintenance of power electronics device.

A budget constraint of MU 15K is assumed for stage 1, and MU 30K is assumed for stage 2. These represent the amount of investment available to the decision maker at each stage.

Table 1: Cost of Required Maintenance

Maintenance Costs	Time Period (Stage) 1	Time Period (Stage) 2
Turbine 1	MU 3.6K	MU 7K
Turbine 2	MU 5.8K	MU 9K
Turbine 3	MU 8K	MU 12.54K
Turbine 4	MU 5.5K	MU 14.5K

Solving equation (2) is analogous to saying that we are minimizing the probability of failure; this will indicate which turbines are to be maintained now given the costs in Table 1.

The problem of having one turbine operating at stage 2 can be formulated as the probability of success of a turbine. A success signifies that a turbine reaches stage 2 with a state e (as illustrated in the Appendix):

$$P(turbine\ 1\ OR\ turbine\ 2\ OR\ turbine\ 3\ OR\ turbine\ 4\ is\ in\ operation\ after\ stage\ 2) = P(turbine\ 1\ succeds) + P(turbine\ 2\ succeeds) + P(turbine\ 3\ succeds) + P(turbine\ 4\ succeds) - \sum_{i\neq j,i,j=1,2,3,4}(turbine\ i\&j\ succeed) + \sum_{i\neq j\neq k,i,j,k=1,2,3,4}(turbine\ i\&j\ \&k\ succeed) - (turbine\ 1\ \&\ turbine\ 2\ \&\ turbine\ 3\ \&\ turbine\ 4\ succeed) \quad (4)$$

The solution of equations (1)-(3) provides the optimal maintenance strategy. It can be equivalently solved with equation (4) which states that at least one turbine should operate by the end of stage 2. At stage 1, the maintenance vessel can only maintain one, two, or a maximum of three turbines. This is cause by the budget constrain of MU 10K. For example, turbines 2 and 3 can be maintained with a cost of MU 13.8 K. Another combination can be turbines 1, 2, and 4 with a cost of MU 14.9K. Similar combinations are chosen at stage 2. The underlying assumption in this hypothetical example is that a turbine has to be maintained in stage 1 in order to be maintained at stage 2. The probability of success is obtained by multiplying the probabilities of reaching state e at stage 2 by the probability of stage 1. For example, the probability of turbine 1 reaching state e at stage 2 is obtained by:

$$P(turbine\ 1\ is\ in\ operation\ after\ stage\ 2) = 0.3 * 0 + 0.2 * 0.1 + 0.3 * 0.3 + 0.2 * 0.6 + 0 * 1 = 0.23.$$

Hence the probability of failure is 0.77. Solving the entire problem results in the optimal strategy of maintaining turbines 3 and 4 in stage 1. This will guarantee that the availability requirement of having at least one turbine functional after stage 2 while meeting the budget constrain.

Conclusions: This paper presents a new real options model to optimize the maintenance of offshore wind turbines where an availability requirement must be met. PHM gives the necessary information for the model by indicating the health of the system. Furthermore, the proposed model can be used for scheduling condition-based maintenance. PHM introduces flexibility in the form of different options available to the decision-maker after a prognostic indication. A mathematical model for the analysis of the option to wait to perform maintenance was formulated. The model is based on stochastic dynamic programming, and identifies the optimal combination of turbines to be maintained in the wind farm when maintenance can be performed. A hypothetical example that shows how the model works was provided. The framework introduced provides promising means for the health management of systems with prognostic capabilities, and can be used to as address several issues: how much extra investment in PHM is justified to meet a specified availability requirement, the cost of maintaining availability requirements, the value in monetary terms that waiting to perform maintenance brings to the decision-maker.

References:

[1] U.S. Department of Energy-Energy Efficiency and Renewable Energy, "20% Wind Energy by 2030, Increasing Wind Energy's Contribution to U.S. Electricity Supply," July 2008

[2] W. Musial and B. Ram, "Large-Scale Offshore Wind Power in the United Sates Assessment of Opportunities and Barriers," National renewable Energy Lab, Technical report, September 2010

[3] M. Schwartz, D. Heimiller, S. Haymes, and W. Musial, "Assessment of Offshore Wind Resources for the United States," National Renewable Energy Lab, Technical report, June 2010

[4] T. Jazouli and P. A. Sandborn, "A 'Design for Availability' Approach for Use with PHM," Proceedings of The Prognostics and Health Management Conference, Portland, OR, October 2010

[5] Z. Hameed, Y.S. Hong, Y.M. Cho, S. Ahn, C.K. Song, "Condition Monitoring and Fault Detection of Wind Turbines and Related Algorithms: A Review," Renewable and Sustainable Energy Reviews, vol. 13, 1-39, 2009

[6] M. Pecht, Prognostics and Health Management of Electronics, Wiley-Interscience, August 2008

[7] S. Cheng, M. Azarian, and M. Pecht, "Sensor Systems for Prognostics and Health Management," Sensors, No. 10, pp.5774-5797, 2010

[8] K. Feldman, T. Jazouli, and P. Sandborn, "A Methodology for Determining the Return on Investment Associated With Prognostics and Health Management," IEEE Transactions on Reliability, Vol. 58, No. 2, June 2009

[9] J. Andrawus, J. Watson, M. Kishk, and A. Adam, "Determining an Appropriate Condition-based Maintenance Strategy for Wind Turbines," The 2nd Joint International Conference on Sustainable Energy and Environment (SEE 2006)

[10] E. Byon, L. Ntaimo, and Y. Ding, “Optimal Maintenance Strategies for Wind Turbine Systems Under Stochastic Weather Conditions,” IEEE Transactions on Reliability, Vol. 59, No. 2, June 2010 393
[11] L. Rademakers, H. Braam, M. Zaaijer, and G. van Bussel, “Assessment and Optimization of Operation and Maintenance of Offshore Wind Turbines,” ECN Wind Energy, Tech. Rep. ECN-RX-03-044, 2003.
[12] T. Copeland and V. Antikarov. Real Options: A Practitioner's Guide. Texere, 2001.
[13] P. Kodukula and C Papudesu, “Project Valuation Using Real Options, a Practitioner’s Guide,” J. Ross Publishing, 2006
[14] A. Borison, “Real Options Analysis: Where are the Emperor’s Clothes?” Journal of Applied Corporate Finance, Vol. 17, No. 2, pp. 17–31, 2005.
[15] J. M. Eckhause, D. R. Hughes, and S. Gabriel, “Evaluating Real Options for Mitigating Technical Risk in Public Sector R&D Acquisitions,” International Journal of Project Management, Vol. 27, pp. 365-377, 2009
[16] S. Gabriel, “Stochastic Dynamic Programming and Real Options,” Probabilistic Optimization, Course Notes, 2010.
[17] K. Dykes and R. de Neufville, “Real Options for a Wind Farm in Wapakoneta, Ohio: Incorporating Uncertainty into Economic Feasibility Studies for Community Wind,” World Wind Energy Conference of 2008, Kingston, Ontario, Canada, June 24-26, 2008
[18] G. V. Bussel, “The development of an expert system for the determination of availability and O&M costs for offshore wind farms,” in 1999 European Wind Energy Conference and Exhibition, Conference Proceedings, Nice, France, 1999, pp. 402–405.

Appendix: The following tables list the transition probabilities assumed for the wind farm example presented in this paper.

Table 3- Transition probabilities

	Stage 1 State	Probability
Turbine 1	a	0.3
	b	0.2
	c	0.3
	d	0.2
	e	0
Turbine 2	a	0.2
	b	0.3
	c	0.4
	d	0.1
	e	0
Turbine 3	a	0.2
	b	0.2
	c	0.3
	d	0.2
	d	0.2
Turbine4	a	0.2
	b	0.3
	c	0.3

	d	0.15
	e	0.05

	State at Stage 2	Given Stage 1	Conditional Probability
Turbine 1	a	a	0.3
	b	a	0.4
	c	a	0.2
	d	a	0.1
	e	a	0
	b	b	0.4
	c	b	0.3
	d	b	0.2
	e	b	0.1
	c	c	0.3
	d	c	0.4
	e	c	0.3
	d	d	0.4
	e	d	0.6
	e	e	1

	State at Stage 2	Given Stage 1	Conditional Probability
Turbine 2	a	a	0.3
	b	a	0.35
	c	a	0.2
	d	a	0.1
	e	a	0.05
	b	b	0.2
	c	b	0.3
	d	b	0.3
	e	b	0.2
	c	c	0.3
	d	c	0.3
	e	c	0.4
	d	d	0.35
	e	d	0.65
	e	e	1

	State at Stage 2	Given Stage 1	Conditional Probability
Turbine 3	a	a	0.2
	b	a	0.3
	b	a	0.3
	d	a	0.15
	e	a	0.05
	b	b	0.3
	c	b	0.4
	d	b	0.2
	e	b	0.1
	c	c	0.4
	d	c	0.3
	e	c	0.3
	d	d	0.5
	e	d	0.5
	e	e	1

	State at Stage 2	Given Stage 1	Conditional Probability
Turbine 4	a	a	0.2
	b	a	0.3
	c	a	0.2
	d	a	0.2
	e	a	0.1
	b	b	0.2
	c	b	0.3
	d	b	0.3
	e	b	0.2
	c	c	0.3
	d	c	0.4
	e	c	0.3
	d	d	0.3
	e	d	0.7
	e	e	1