

Review of Markov Models for Maintenance Optimization in the Context of Offshore Wind

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ABSTRACT

The offshore environment poses a number of challenges to wind farm operators. Harsher climatic conditions typically result in lower reliability while challenges in accessibility make maintenance difficult. One of the ways to improve availability is to optimize the Operation and Maintenance (O&M) actions such as scheduled, corrective and proactive maintenance. Many authors have attempted to model or optimize O&M through the use of Markov models. Two examples of Markov models, Hidden Markov Models (HMMs) and Partially Observable Markov Decision Processes (POMDPs) are investigated in this paper. In general, Markov models are a powerful statistical tool, which has been successfully applied for component diagnostics, prognostics and maintenance optimization across a range of industries. This paper discusses the suitability of these models to the offshore wind industry. Existing models which have been created for the wind industry are critically reviewed and discussed. As there is little evidence of widespread application of these models, this paper aims to highlight the key factors required for successful application of Markov models to practical problems. From this, the paper identifies the necessary theoretical and practical gaps that must be resolved in order to gain broad acceptance of Markov models to support O&M decision making in the offshore wind industry.

1. INTRODUCTION

Offshore wind turbines will play a key part in meeting the UK's renewable energy targets in the future. The US Department of Energy also anticipates a sharp increase in the number of offshore wind farms (US DoE, 2008).

However, the offshore wind turbine energy yield in the UK is still badly affected by low availabilities, which have been shown to be around 80.2%, compared to 97% onshore (Feng, Tavner, & Long, 2004). Enabling operators to effectively plan for repairs and inspections would likely improve the availabilities. There has been research (Pahlke, 2007) showing there is significant demand for decision support systems in the offshore wind industry. It was reported that 99% of mechanical failures are preceded by noticeable indicators (Lee, Ni, Sarangapani, Mathew, 2011). Fully utilizing Condition Monitoring (CM) data can lead to improved diagnosis and prognosis, yet some authors argue that the wind industry is not taking the full advantage of it (Cibulka, Ebbesen, Hovland, Robbersmyr, & Hansen, 2012). Attempts have been made to quantify the benefits of monitoring systems for wind turbines (McMillan & Ault, 2007), concluding that rewards of having a CM system outweigh the costs in most cases.

Offshore wind farm operators' actions are constrained by logistics and the weather, which makes optimizing O&M difficult (Van Horenbeek, Van Ostaeyen, Duflou, & Pintelon, 2013). High complexity of many wind turbine components and the environment they operate in often means that a number of failure modes exists, hindering effective failure prediction (Fischer, Besnard, & Bertling, 2012). Although there has been a significant amount of work done on maintenance optimization models, both in the wind sector and other industries, there is little evidence of successful application of these models in the offshore wind sector. Markov models have been successfully applied to diagnosis, prognosis and maintenance optimization in other industries, with significant effort being invested to implement them in the wind sector. The purpose of this study is to provide an overview of the work done on O&M optimization, focusing specifically on the use of Markov models, in the context of the offshore wind industry.

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2. RELATED REVIEWS

2.1. Wind Industry

There have been a number of review papers related to maintenance optimization models, but only a few of them are focused on the wind industry. Welte and Wang (2013) outlined different types of lifetime estimation models, while providing examples of their application to the wind industry. Hofmann (2011) identified 49 models on different aspects across the whole life-cycle of the wind farm, from planning and construction to O&M. However, little information is provided on the inner workings of those models. Moreover, a number of those models are shrouded by commercial interest of the companies who own them, making it difficult to investigate their effectiveness and the methods used.

El-Thalji (2012) provided a comprehensive review of the O&M practices of wind power assets, highlighting that the main issues in offshore wind maintenance lie with site accessibility and environmental factors. Cibulka et al. (2012) provided an insight into the failure modes of different wind turbine components; methods of monitoring different electrical, mechanical and fluid parameters were also reviewed. The paper concluded that the wind turbine industry lacks pro-active use of CM data for estimating the remaining life of components. Finally, Hameed, Hong, Cho, Ahn and Song (2009) provided a comprehensive review of various CM approaches for wind turbine industry.

The aforementioned review papers provide a solid background of the offshore wind maintenance practices and shed some light on the approaches used so far, but no detailed description of the models was provided. However, there is no lack of review papers on the use of Markov models for maintenance in other industries; these are described in the following section.

2.2. Other Industries

Optimizing maintenance using mathematical models is by no means a novel approach; a significant amount of work was done on maintenance optimization models from 1970's until early the 90's, yielding numerous review papers (Pierskalla & Voekler, 1976)(Sherif & Smith, 1981)(Monahan, 1982)(Valdez-Flores & Feldman, 1989)(Cho & Parlar, 1991)(Wijnmalen & Hontelez, 1992). Monahan's review is particularly noteworthy as his POMDP framework and algorithms for computing optimum policies have been quoted and applied numerous times by many researchers in the field of maintenance optimization.

A more recent study by Dekker (1996) reviewed maintenance optimization models, mostly concerning vehicle replacement, road maintenance and power stations. The paper identified 43 case studies, some utilizing Markov models, in which the models were based on real data and the

outcome of the model advised decision making. Despite identifying a large number of related case studies, little attention was given to critical analysis of the different approaches used. A brief review of software used for maintenance optimization was also provided, but given that the paper was written almost 20 years ago, most of them are now obsolete. Amongst the 132 references in this paper, there was not a single one on the subject of wind energy. According to Frangopol, Kallen and Noortwijk (2004), Markov models are the most common method of modelling bridge maintenance. The authors also highlighted the need to incorporate the data from imperfect inspections in deterioration systems.

Deterioration prognostic models are a large part of decision support tools. For a prognostic model to be effective, it needs to be able to predict the component's condition sufficiently far into the future to facilitate preparation of spares and human resources (Heng, Zhang, Tan, & Mathew, 2009). Heng et al. have also stressed that most studies on rotating machinery are done in labs, neglecting practical considerations such as interactions between components and the impact of weather. Tung and Yang (2009) provided another comprehensive review paper on rotating machinery prognostics, highlighting that physical model-based approaches are not suitable for complex systems. The authors also stated that the lack of industrial application of prognostic models is partly due to the complexity of a real-life machine, hindering accurate modelling and hence reducing the accuracy of predictions. The use of Markov models for remaining useful life estimation was reviewed by Si, Wang, Hu and Zhou (2011). The authors highlighted the challenges of capturing the influence of external variables, as well as modelling multiple failure modes for the same component.

Peng, Dong and Zuo (2010) argue that combining 2 or more different prognostic approaches may increase the precision, reduce the computational time and combine the benefits of the different approaches while nullifying their demerits. The authors highlighted the fact that HMMs are easily realizable in software. They also stated that most research in the area is still in the theoretical phase, few of the models have been applied in practice. Scarf (1997) stated that "too much attention is paid to the invention of new models, with little thought, it seems, as to their applicability". The author also argues that many models are over-complicated, making them hard to follow by the practitioners. Zio (2009) and Kothamasu, Huang and Verduin (2009) also recommended that the implementation of reliability methods should be supported by reasonably user-friendly software.

Dragomir, Gouriveau, Minca and Zerhouni (2009) provided a brief review gathering papers on various prognostic algorithms, stating that real prognostic models are scarce in the industry while Tung (Tung & Yang, 2009) pointed out that the amount of research done on prognosis is much less

compared to diagnosis. A large proportion of papers reviewed in (Wang, 2002) involve maintenance policies based on age or fixed time intervals. Such approaches lack depth and flexibility and hence are not suitable for the offshore wind industry. Vasili, Hong and Ismail (2011) rightly concluded that there is a need to develop approaches which will optimize maintenance, while also considering different aspects of the maintenance management. This is especially true for the wind industry, whereby the factors such as weather and logistics are paramount to successful planning of maintenance strategy.

Nicolai and Dekker (2008) focused on multi-component approach to modelling, which has the potential to capture dependencies between components but potentially over-complicates the model. Kothamasu et al. (2009) looked into different techniques of system health monitoring and their use for prognosis to improve reliability, including some Markov models. Reinertsen (1996) reviewed a number of models with practical applications but found no models that could be applied, generally, to a broader range of problems. The author called for more consistency in the industry when applying methods for assessment of deterioration and residual life of structures.

The majority of the papers discussed in this section reviewed Markov models, but only a few were solely focused on them. The next section presents an overview of theoretical and practical Markov models for maintenance optimization.

3. MARKOV MODELS

Markov Models can be broadly split into Markov chains, Markov Decision Processes (MDPs), Hidden Markov Models (HMMs) and Partially Observable Markov Decision Processes (POMDPs), which are described in the following sections. Table 1 in the Appendix contains a summary of Markov models for maintenance optimization referenced in this paper, grouped by the method used and application.

3.1. Markov Chains and Markov Decision Processes

Markov chain is a random process, wherein a probability of transition between states only depends on the current state, not on the sequence of previous events. Markov chains have been used for modelling offshore wind O&M (Özdirik, Skiba, Würtz, Kaltschmitt, & Williams, 2013), in a paper which discusses a number of limitations associated with maintenance of offshore wind farms. Yang, Kwan and Chang (2008) used Markov chains to simulate deterioration of electrical substation components, while a multiobjective evolutionary algorithm was used to provide the user with a number of Pareto curves, facilitating visualization of the trade-offs between overall costs and expected unserved energy. Markov chains have been used to model wind turbine blade deterioration in a study by Besnard and Bertling (2010) which also compared the costs and benefits

of using a condition monitoring techniques versus inspections, favoring the former approach.

Wilson and McMillan (2014) used Markov chains and Monte Carlo method for assessing reliability of potential wind farm sites, providing a forecast of future O&M costs. Lee, Li and Ni (2013) argued that equipment operators can be quite conservative when setting the maintenance intervals. By applying Markov models to a semiconductor manufacturing process data it was shown that significant maintenance cost savings can be obtained by increasing the time between maintenance actions.

Semi-Markov models relax the assumption of constant transition probabilities, which is more representative of most engineering systems. They have been used in modelling deterioration (Kleiner, 2001) (Black, Brint, & Brailsford, 2005); the latter research showing that maintenance cost savings can be obtained using this method, given sufficient amount of past deterioration data. Semi-Markov approach was also applied to 2-unit standby systems by Maksoud and Moustafa (2009) and Zhong and Jin (2014), wherein the optimal policy for the former was obtained using an iterative process, while the latter utilized Laplace Transform to solve Markov renewal equations, yielding optimal maintenance policy. A different study (Kharoufeh, Solo, & Ulukus, 2010) used a semi-Markov model to assess the current and future states of a system, taking into account the environmental factors. A framework for asset management of power distribution networks based on Semi-Markov models was proposed by Johnson, Strachan and Ault (2012). The authors argue that the component's future deterioration can be predicted without any historical data by using condition health indices.

MDPs are an extension of a Markov chain, with the addition of the possibility of taking actions, each with associated cost or reward. The timing, order and choice of actions can then be optimized for a given parameter, usually to minimize the cost. Shafiee (2015) defined the 3 main echelons of decision making for offshore wind; namely strategic (long term), tactical (medium term) and operational (short term). Maintenance optimization models would aim to aid operational decisions through maintenance scheduling and planning of logistics; they could also have some impact on the tactical decisions – for example spare part management or maintenance support organization.

Chan and Asgarpoor (2006) provided a simple example of how an MDP can be used to find the optimal mean time to preventative maintenance. Nielsen and Sørensen (2014) conducted a comparison of different approaches to decision support, concluding that MDP is the most accurate method of optimizing the decision policy, with great potential for application in offshore wind industry. The same authors (Nielsen & Sørensen, 2012) have also shown that an MDP can be easily adapted to take external factors such as weather and vessel rental costs into account. This opens up

possibilities of further O&M cost savings, for example by using clustering of repairs.

Semi-Markov Decision Processes (SMDPs) have also been applied in optimizing the inspection and maintenance schedule (Chen & Trivedi, 2005) (Amari & McLaughlin, 2006), with the latter model being very simple but effective, meaning it could be easily adapted to a given practical problem. Berenguer, Chu and Grall (1997) used an SMDP for optimization of inspection and maintenance; although their model may be more realistic for some systems compared to other MDP approaches, the authors admit it is difficult to exploit it analytically due to its complexity. Kahrobaee and Asgarpour (2013) proposed an approach for maintenance optimization based on SMDPs, which was applied to a case study of wind turbines. Once the optimal repair policy was found, a Monte Carlo simulation was used to investigate how the wind turbine availability varies with different factors such as the number of repair technicians employed.

The majority of the papers referenced in this section provide numerical examples, which are useful in understanding and assessing the model's capabilities, but are no match for validation through an application to an actual problem. Although computationally effective, simple Markov models assume that the exact state of the component is known, which is rarely the case with offshore wind turbines. This assumption is relaxed through the use of HMMs, as described in the following section.

3.2. Hidden Markov Models

Wind turbine CM data provides valuable information on the state of various components, however, the degree of system's deterioration is usually difficult to predict with certainty. In HMMs, the current state of the component is represented by a probability distribution, making it a very functional tool for wind turbine deterioration modelling, diagnosis and prognosis.

Detection of machine failure using HMMs was investigated by Tai, Ching and Chan (2009). Qian, Jiao, Hu and Yan (2007) trained HMMs using a Baum-Welch algorithm to diagnose the type of fault in large scale power transformers. A different approach to diagnosis was suggested by Kwan, Zhang, Xu and Haynes, (2003) and Zhang, Xu, Kwan, Liang, Xie, and Haynes (2005). In both papers, multiple HMMs were created for different failure modes. The HMM with the highest probability of being in a failed state was used to identify the failure mode. Such approach is particularly useful for systems which have more than one likely failure mode, as is often the case with wind turbine components. Both studies have been based on experimental data and the algorithms have also shown prognostic capabilities. Ghasemi, Yacout and Ouali (2007) have used HMMs to simulate deterioration in their model which

calculates the long-run average operating costs for strategies with different observation intervals.

HMM-based clustering was used by Chinnam and Baruah (2003) for diagnostics and prognostics. Numerous HMMs were constructed and tested with 3 best performers being selected to diagnose the condition of the asset. A multivariate distribution of the state transition points generated by HMMs was then used for prognosis. Zhou, Hu, Xu, Chen and Zhou (2010) proposed a HMM for real time failure prognosis. Expert knowledge was incorporated into the model through belief rules to capture the influence of environmental factors. The model shows great potential for application in offshore wind, as it is capable of considering the environmental and logistical factors, however the authors did admit that further testing is required to validate the model. HMM approach has also been used in decision making support tool for offshore wind called ECUME (Douard, Domecq, & Lair, 2012).

Research by Dong (2008) used an Auto-Regressive Hidden Semi-Markov Model, which has a few advantages over a standard HMM; namely it does not follow the standard Markov memory-less approach, it also relaxes the assumption of independent observations. The algorithm was tested on a case study of hydraulic pumps and shown good health state recognition rates, with the possibility of application for prognostics. The same author has also applied Hidden Semi-Markov Model (HSMM) methodology for diagnostics and prognostics in his earlier work on hydraulic pumps (Dong & He, 2007) and helicopter transmission system (Dong, He, Banerjee, & Keller, 2006), showing that HSMMs are more effective at current state recognition than HMMs. Recent work by Cartella, Lemeire, Dimiccoli and Sahli (2015) used the HSMM methodology for remaining useful life estimation of bearings. The model was validated using real life vibration data and produced reasonably accurate results (although bearings under lab conditions do exhibit monotonically increasing degradation pattern making it easier to predict). One of the advantages of the approach presented in this paper is that it allows the use of both discrete and continuous observations.

It is worth noting that a large proportion of models reviewed in this section were based on experimental data, which is an improvement over validation approaches through numerical examples and simulations. However, as stated by Heng et al. (2009), lab tests fail to capture many practical considerations. The models described above are capable of deterioration modelling, diagnosis and often prognosis, however, they lack the decision making capability. POMDPs combine the hidden property of the Markov model with the ability to consider various maintenance actions and implications, resulting in a powerful maintenance optimization tool.

3.3. Partially Observable Markov Decision Processes

Early theoretical research by White (1976), Rosenfield (1976) and Monahan (1982) have laid the groundwork for many more recent POMDP models. Since then, a number of other papers presenting theoretical frameworks for the application of POMDPs to the maintenance problem have been published (Madanat, 1993)(David, Friedman, & Sinuany-Stern, 1999)(Makis & Jiang, 2003)(Maillart, 2006). The contribution of these papers to the field of maintenance optimization is without a doubt substantial, however, many researchers are reluctant to apply those frameworks, instead opting to use their own approaches.

Byon and Ding (2010) created a model for the offshore wind industry, which emphasizes the importance of the seasonal weather variation on wind turbine availability. A POMDP model was solved by backward dynamic programming method. It was shown that by using the proposed approach, the maintenance costs over the lifetime of a wind turbine can be reduced significantly compared to both periodic maintenance and condition-based maintenance strategy which does not take into account the seasonal variation. The model could be improved by considering the logistical issues specific to the offshore wind industry such as long lead times on parts and vessels. These factors were given more thought in Byon's related article (Byon, Ntaimo, & Ding, 2010), which highlights the importance of condition-based monitoring, yet it fails to incorporate the CM data into the model. Dynamic programming method applied by Byon and Ding (2010) is computationally intensive for large problems. It was suggested that the application of a tractable approximation scheme can shorten the computational effort required, while still considering dynamic weather changes (Byon, 2012).

Papakonstantinou and Shinozuka conducted a two part study focused on the use of POMDPs for planning structural inspection and maintenance. Part 1 (Papakonstantinou & Shinozuka, 2014a) highlights the difficulties of solving POMDPs for complex problems, while providing practical solutions. Part 2 (Papakonstantinou & Shinozuka, 2014b) applies the theory from part 1 to a case study on corroding reinforced concrete structure. The model yields a highly complex optimum policy, which, according to the authors, could not have been reached by any other method. The framework used in the two part study is very promising; however the complexity of the model may hinder its applicability. The authors argue that exact solution for a POMDP would be too computationally intensive to solve for large problems and propose an approximate value iteration method instead, which is much more effective dealing with large problems (Papakonstantinou & Shinozuka, 2014c).

AIDurgam and Duffuaa (2012) used a POMDP model to generate policy graphs, which allow the operator to choose the optimal maintenance action and speed setting given the

current belief state of the component. Fan, Xu and Chen (2013) and Chen, Fan, Hu and Zhou (2014) investigated repair optimization for systems with imperfect maintenance; they also argue that limiting the number of times a component can be repaired and imposing quicker deterioration on components which have already been repaired multiple times is more representative of engineering systems. The authors have also stated that their work needs extending to include condition-based maintenance through the use of sensor data, which would be particularly applicable for the wind industry.

Srinivasan and Parlikad (2014) combined the advantages of an SMDP and POMDP by creating a Partially Observable Semi-Markov Decision Process (POSMDP) for optimum maintenance decision making. Through the use of belief state, the POSMDP is converted into a SMDP. This approach allows the use of different failure rate distributions, facilitating the method's potential application to various wind turbine components. A different approach to POSMDPs was used by Zhou, Ma, Matthew, Sun and Wolff (2010). In their research, degradation is modelled using a Gamma-based state-space approach. The model is based on continuous POSMDP, which is then converted to a fully observable SMDP through an application of Monte Carlo-based density projection method to optimize maintenance decision making.

Standard POMDPs require set values of transition and emission probabilities, but there is often an uncertainty associated with those. Memarzadeh, Pozzi and Kolter (2013) propose a Bayes-adaptive POMDP methodology, which treats conditional probabilities as random variables. This can result in the optimal policy being sub-optimal for any specific value of transition and emission probabilities, instead maximizing the value for the entire state. A wind farm case study based on synthetic data showed that this methodology can be more effective than a standard POMDP approach, especially for problems with high conditional probability uncertainty.

POMDPs have also been used in the context of civil engineering. Jiang, Corotis and Ellis (2000) developed a model which considered fatigue and corrosion as main deterioration processes of a steel girder highway bridge. A detailed example of the model's application is provided, which, despite considering 5 maintenance action types and 4 inspection strategies, remains computationally effective. Later work by the same authors (Corotis, Ellis, & Jiang, 2005) presented POMDP theory and an algorithm for the optimal management and design of structures. Ivy and Pollock (2005) attempted to optimize maintenance on a system with "silent failures": i.e. a system in which the component can remain operational despite it being in a failed state, with an increased cost being incurred on its operation.

POMDPs and POSMDPs are modelling tools with a number of advantages: they are capable of dealing with imperfect observations, allow flexibility in terms of the choice of maintenance action and deterioration mechanism, are capable of modelling multiple failure modes and have been shown to be able to consider external factors such as weather and logistics in making the optimal decision, making them a suitable methodology choice for successful application to the maintenance problem in the wind industry.

4. CONCLUSIONS

This review paper focused on the use of Markov models for deterioration modelling and maintenance optimization in a wide range of industries. Given a projected threefold increase in UK offshore wind O&M spend in the next 10 years (GL Garrad Hassan, 2013), the application of such models will play an important role in keeping the costs of energy low. The main conclusions of this paper are as follows:

- The majority of the models reviewed in this paper have either been validated by lab tests or, in many cases, their capabilities were shown using simple numerical examples/simulations. Very few models have actually been applied in the industrial environment. Other researchers in the field have suggested more emphasis should be placed on application of the existing models rather than invention of new models.
- A large number of the models discussed in this paper contain a sound framework which could be successfully applied to the wind industry, provided significant adaptation was carried out, which would involve ensuring that factors such as access restrictions due to weather and logistical issues are considered.
- One of the constraints to widespread Markov models application in the offshore wind industry could be their complexity. Other researchers in the maintenance optimization field have stated that practitioners are unlikely to apply over-complicated models.
- Some researchers have touched upon the computational constraints of Markov models (Tai et al., 2009) (Papakonstantinou & Shinozuka, 2014b). Although HMMs and POMDPs are effective for small state spaces, it was indicated that computational factors may become prohibitive for larger and more complex systems, especially when the methodologies are applied to wind farm-scale problems. In an attempt to address this issue, researchers started to explore more computationally effective ways of solving POMDPs (Byon, 2012) (Papakonstantinou & Shinozuka, 2014c).
- Some of the interesting concepts which have not been researched in depth within the Markov model framework, but may be useful for offshore wind are: opportunistic maintenance, the silent failure approach

and de-rating to potentially slow down the degradation process if the turbine cannot be accessed.

The majority of the papers reviewed here focus on the maintenance of mechanical, electrical or structural systems, which all can be applied to offshore wind turbines. However, the offshore environment, where the majority of UK wind turbines will be built in near future, poses numerous challenges to wind farm operators. Research conducted for other industries often ignores issues such as access restrictions, offshore logistics and the high costs associated with it and the problem of effective utilization of large volumes of CM data for deterioration modelling and maintenance optimization. Although it has been shown by some authors that these challenges can be tackled through the use of Markov models, no comprehensive framework exists capable of considering all these factors. The focus of researchers working on O&M for offshore wind should be to attempt to create such framework. As shown in this, and other review papers, methodologies exist to fit most offshore maintenance problems; the biggest challenge now is to work with practitioners to apply those models to real engineering problems.

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APPENDIX

Table 1. Markov models by industry and method used^{1,2}

	Wind industry	General applications	Electrical systems	Civil engineering	Mechanical/ Manufacturing
Markov Chain	(Wilson, 2014) (Özdirik, 2013) ^{MU} (Besnard, 2010)	(Lee, 2013) ^{MU}	(Yang, 2008) ^{MU}		
Semi-Markov Chain	(Kharoufeh, 2010)	(Zhong, 2014) ^{MU} (Maksoud, 2009) ^{MU}	(Johnson, 2012)	(Black, 2005) (Kleiner, 2001) ^{IO}	
MDP	(Nielsen, 2014) ^{IO}		(Chan, 2006)		
SMDP	(Kahrobaee, 2013)	(Amari, 2006) (Chen, 2005) (Berenguer, 1997)			
HMM	(Douard, 2012)	(Zhou, 2010a) (Ghasemi, 2007) ^{IO}	(Qian, 2007)		(Tai, 2009) ^{MU} (Zhang et al., 2005) (Kwan, 2003) (Chinnam, 2003)
HSMM					(Cartella, 2015) (Dong, 2008) (Dong, 2007) (Dong, 2006)
POMDP	(Memarzadeh, 2013) ^{IO} (Byon, 2010) ^{IO}	(Chen, 2014) ^{IO} (Fan, 2013) (AlDurgam, 2012) (Maillart, 2006) ^{IO} (Ivy, 2005) ^{IO} (David, 1999)		(Papakonstantinou, 2014b) ^{IO} (Corotis, 2005) ^{IO} (Jiang, 2000) ^{IO} (Madanat, 1993)	
POSMDP		(Srinivasan, 2014) ^{IO} (Zhou, 2010b) ^{IO}			

IO – Imperfect Observations: uncertainty associated with the action of observation/inspection.

MU – Multi-Unit: models formulated specifically for multi-unit systems (rather than models capable of considering multiple components).

¹ For clarity, the references have been shortened to 1st author and year of publication only.

² This table contains a quick reference for the reader, consolidating the articles mentioned in the body of the paper. It is not a comprehensive list of all Markov models within these industries.