A BAYESIAN UPDATING FRAMEWORK FOR SIMULATING MARINE ENERGY CONVERTER DRIVE TRAIN RELIABILITY

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INTRODUCTION

Accurately quantifying and assessing the reliability of Marine Energy Converters (MEC's) is critical for the successful commercialization of the industry. Without improvements in reliability and hence reductions in operation & maintenance (O&M) costs, the industry will struggle to reach competitive Levelised Cost of Energy (LCoE). At present, due to the nascent stage of the industry and commercial sensitivities there is very little reliability field data available. This presents an issue: how can the reliability of MEC devices be accurately assessed and predicted with a lack of specific reliability data?

BACKGROUND

Reliability prediction in the MEC industry often uses surrogate data sources which are corrected for the marine environment via correction factors [1], [2], [3]. The surrogate data is typically sourced from component specific field tests out with the marine environment [3], [4] or from onshore wind databases [5], [6]. Typically, the resulting estimates are time independent and thus assume that individual components exhibit random failures (constant failure rate).

Reliability prediction is inherently an uncertain process; the traditional statistical methods typically used in MEC reliability assessments do not contain a measure of this uncertainty. Thus, reliability assessments of MEC devices tend to be uncertain as well as being based on data sources that are often outdated and not specific to the marine environment.

This paper seeks to develop a Bayesian updating framework for critical drive train components using high fidelity onshore wind failure data. This framework can then have MEC field data applied to as it becomes available.

Bayesian updating is a statistical method that offers an opportunity to address uncertainty and lack of specific data issues. It has distinct advantages over classical probabilistic methods. Its primary goal is to define the uncertainty surrounding the unknown parameters of a statistical model. Given that there is currently no publicly available reliability field data for MEC's, Bayesian updating presents a promising way in which to perform more accurate reliability assessments.

Bayesian updating has the advantage of being able to make predictions about future performance despite having access to little or no data. This is particularly attractive for an industry such as marine renewable energy. Also Bayesian updating allows for multiple, disparate sources of data to be incorporated into the analysis whilst providing an inherent, subjective measure of the uncertainty surrounding a statistical parameter. This can have profound implications for MEC reliability assessment as it enables a degree of belief to be assigned to a statistical parameter thereby providing a quantified level of certainty in the values underpinning reliability assessments.

Current work on MEC reliability prediction that uses Bayesian methods includes [7] which uses the inherent quantification of uncertainty that Bayesian methods possess to address the uncertainty in the failure rates of a notional wave energy converter power cable. The underlying failure data here is from OREDA and assumes a constant failure rate for the power cable.

Also [2] uses a Bayesian framework for its analysis of mechanical drive train failure rates for a notional tidal turbine, focusing on analyzing the effect of the number of failures and strength of belief on component failure rates.

This paper furthers the ideas presented in these two studies via the application of high fidelity surrogate failure data and builds a framework that defines the uncertainty around the unknown parameters of component failure models and can be used to apply MEC field data as it becomes available.

Experience from onshore wind has shown that the drive train is a critical area with respect to reliability [8]. The Pitch System and Generator often record the highest number of failures so these components are where the focus of this paper lies.

BAYESIAN THEORY AND RELIABILITY DATA

Bayesian analysis involves the determination of probability density functions (PDF's) that define the uncertainty around statistical parameters of interest.

The prior distribution represents all knowledge that exists about an unknown statistical parameter of interest prior to any formulation of an experiment. Typically, this constitutes engineering knowledge and/or data from surrogate industries.

A 2 parameter Weibull distribution is chosen to represent the probabilistic failure model for each component due to its flexibility and common application with failure statistics (Equation 1).

$$p(t|\eta,\beta) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^{\beta}} \quad (1)$$

t represents the time to first failure (TTFF) for the component. The unknown parameters of the distribution (β, shape and η, scale) can be modelled as random variables and represented by 2 parameter Weibull distributions:

$$p(\beta|a_\beta, b_\beta) = \frac{b_\beta}{a_\beta}\left(\frac{\beta}{a_\beta}\right)^{b_\beta-1} e^{-\left(\frac{\beta}{a_\beta}\right)^{b_\beta}} \quad (2)$$

$$p(\eta|a_\eta, b_\eta) = \frac{b_\eta}{a_\eta}\left(\frac{\eta}{a_\eta}\right)^{b_\eta-1} e^{-\left(\frac{\eta}{a_\eta}\right)^{b_\eta}} \quad (3)$$

Where a_β and b_β are the scale and shape parameters of the prior shape parameter distribution, a_η and b_η are the scale and shape parameters of the prior scale parameter distribution. The goodness of fit of the distribution to failure time data can be seen for the Pitch System in Figure 1.

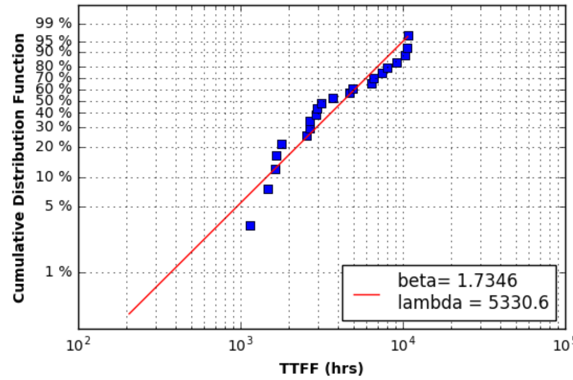

FIGURE 1 WEIBULL PROBABILITY PLOT FOR PITCH SYSTEM FAILURE TIME DATA

The data underlying the prior distributions comes from the Reliawind project, described in reference [8]. This high fidelity onshore wind failure data comes from several different wind farms in the United Kingdom. This paper uses failure events for the pitch system and generator from all the turbines in four farms (in total over 100 turbines). The turbines are the same model and are rated between 1-2MW which is comparable to those deployed in early MEC arrays. The generators are of the Doubly Fed Induction (DFIG) type and the pitch systems are electric.

The likelihood function is used to update the prior distributions and is of the same functional form (a 2 parameter Weibull distribution) as the priors.

Applying Bayes theorem:

$$p(\beta,\eta|t) = \frac{f(t|\beta,\eta)\, p(\beta)p(\eta)}{\iint f(t|\beta,\eta)\, p(\beta)p(\eta)\, d(\beta)\, d(\eta)} \quad (4)$$

results in the definition of two posterior distributions $p(\beta|t)$ and $p(\eta|t)$ which provide information about the uncertainty around the unknown statistical parameters β and η. The double integral must be evaluated using a Markov Chain Monte Carlo (MCMC) numerical algorithm e.g. Metropolis-Hastings.

METHOD

This paper demonstrates the development of a Bayesian updating framework that can be applied in the reliability assessment of MEC's. The method used is as follows:

1. Calculate maximum likelihood estimates (MLE) of component failure models for each of the four windfarms

2. Fit a 2 parameter Weibull distribution to the MLE estimates for each component. This represents the prior distributions of the unknown parameters of the component failure models
3. Fit 2 parameter Weibull distribution to likelihood data (the 'new' data representing field data).
4. Compute posterior distributions of unknown parameters using Metropolis Hastings algorithm
5. Use mean values from posteriors as parameters in component failure models

Firstly, MLE's of the unknown parameters of the component failure models are obtained for each of the four windfarms. Given that each farm has between 10-40 turbines of the same model and the failure data used is consistently from the first 6 months of operation it is reasonable to assume that the unknown parameters for each farms components come from the same distributions. This is the rationale behind obtaining the parameters via MLE and then fitting a distribution to them. There are only 4 points for each fit and this is acknowledged as a limitation of the available dataset.

The likelihood function constitutes the next 6 months of data for each of the turbines in each farm. This represents a bi-annual updating program in which the existing data is updated at scheduled 6 monthly intervals. Given the nature of typical MEC scheduled maintenance regimes this is not unreasonable.

The Metropolis Hastings algorithm is then used (a subset of Markov Chain Monte Carlo (MCMC) methods) to generate the posterior distributions which completely define the uncertainty around the unknown statistical parameters β and η.

The mean values of the parameter posterior distributions are then used to determine the updated component reliabilities. These updated reliabilities are compared with the initial component reliabilities obtained using mean values of the prior distributions of the unknown parameters. This allows for the effect of the parameter update on the component reliability to be examined.

This paper currently only uses onshore wind data; however, it proposes a framework that can be used to apply MEC field data directly as it becomes available. This framework also allows for investigations into the effects of using different subsets of data e.g. size and type of turbine. Thus, the effects on the evolving data set can be used to inform decision making for MEC maintenance operations for different ratings of pitch system and generator.

It is acknowledged that the drive train of an MEC consists of more than the two components investigated here, but the framework that the paper proposes allows for further components to be incorporated as necessary.

RESULTS

The prior distributions for η and β can be seen in figures 2 and 3 respectively.

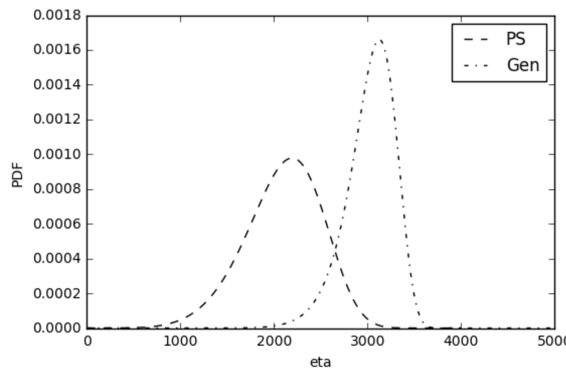

FIGURE 2 PRIOR PDF FOR ETA PARAMETER OF FAILURE MODELS FOR PS: PITCH SYSTEM, GEN: GENERATOR

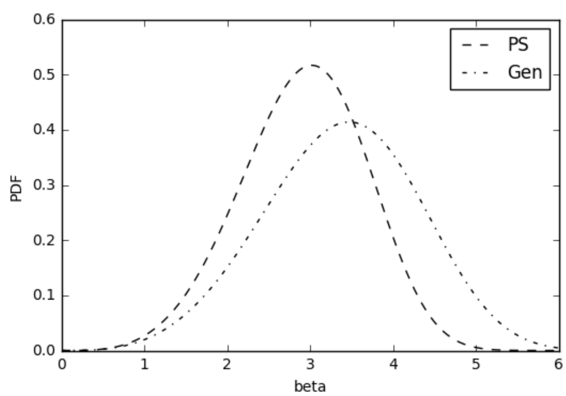

FIGURE 3 PRIOR PDF FOR BETA PARAMETER OF FAILURE MODELS FOR PS: PITCH SYSTEM, GEN: GENERATOR

The concentration of mass is more pronounced for the Generator than for the Pitch System for the η parameter (as shown in figure 1). This is because the underlying data (the MLE shape parameters for the generators for each farm) are similar in value and not as dispersed as for the pitch systems.

The posterior distributions for each parameter can be seen in figures 4 and 5. These are the result of 200,000 drawn samples.

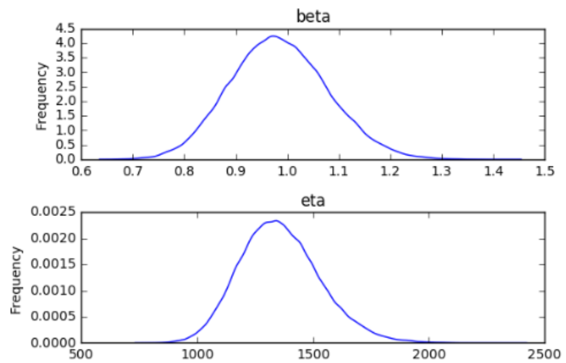

FIGURE 4 POSTERIOR DISTRIBUTIONS FOR BETA AND ETA FOR PITCH SYSTEM

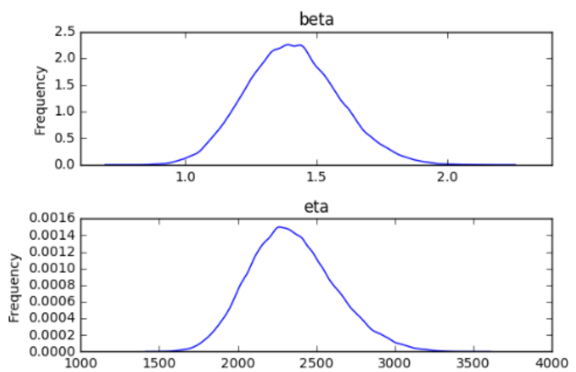

FIGURE 5 POSTERIOR DISTRIBUTIONS FOR BETA AND ETA FOR GENERATOR

The mean value parameters and Highest Posterior Densities (HPD) are shown for each parameter and component in Table 1.

TABLE 1 MEAN VALUES, HIGH POSTERIOR DENSITIES FOR UNKNOWN PARAMETERS FOR EACH COMPONENT

	β(mean)	η(mean)	95% HPD (β)	95% HPD (η)
Pitch System	0.98	1356	0.80-1.17	1032-1706
Generator	1.41	2347	1.07-1.76	1841-2925

The HPD is analogous to a classical confidence interval and can be interpreted as defining with 95% certainty the possible values the random variables (unknowns β and η) can take.

Implementing the mean values of the parameters into the component reliability models (from Equation 1) yields the plots in Figures 5 and 6.

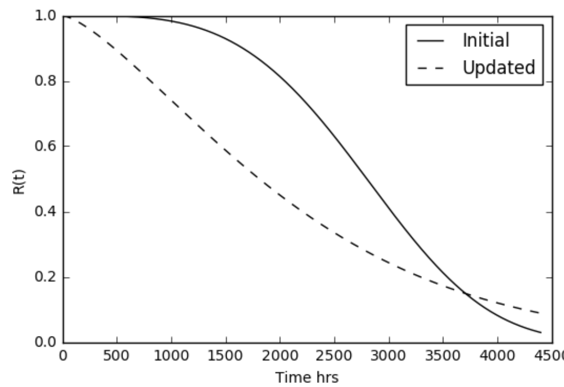

FIGURE 6 GENERATOR PROJECTED RELIABILITY, INITIALLY AND AFTER UPDATE

These plots can be viewed as projected component reliability models using initial data parameters and then updated parameters.

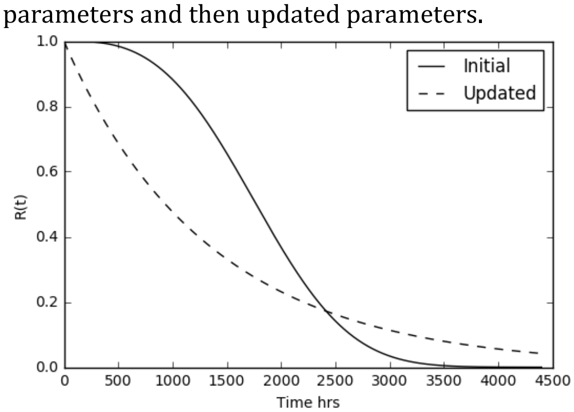

FIGURE 7 GENERATOR PROJECTED RELIABILITY, INITIALLY AND AFTER UPDATE

For both components, updating the parameters after 6 months results in a much changed reliability model.

CONCLUSIONS

The Bayesian updating framework developed in this paper uses high fidelity onshore wind failure data to form prior distributions of the unknown parameters of component failure models. It updates this information with the next 6 months of failure data to provide the framework for MEC's to perform scheduled updating of component failure models when field data becomes available.

The effect that parameter updating has on component reliability models has been demonstrated for a pitch system and generator from a 1-2MW onshore wind turbine.

The framework developed here can provide MEC developers, project stakeholders and insurers with a method of quantifying the uncertainty surrounding the unknown statistical parameters of component reliability models.

ACKNOWLEDGEMENTS

The support of the ETI and RCUK Energy Program funding for IDCORE (EP/J500847/1) is gratefully acknowledged.

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