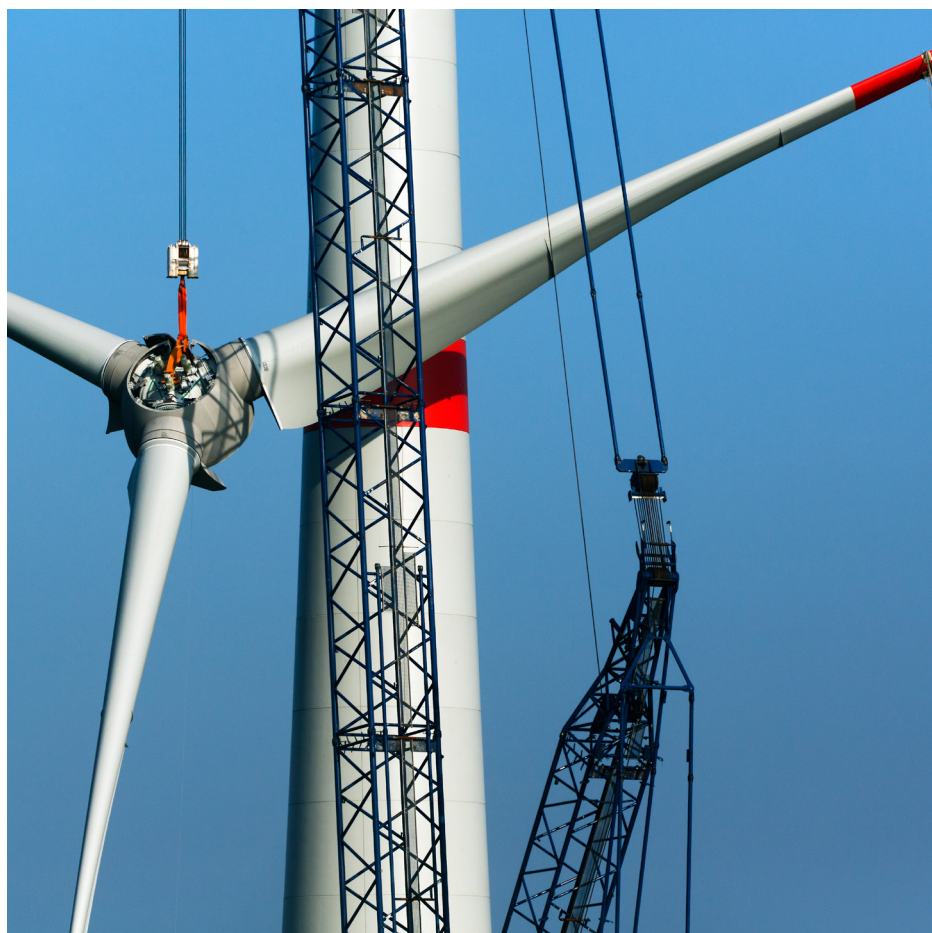
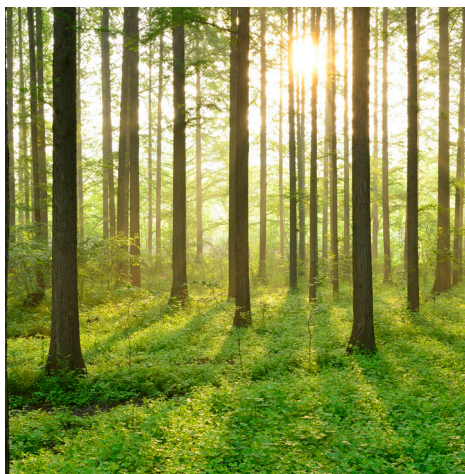


# BAYESIAN METHODS FOR PREVENTIVE MAINTENANCE

REPORT 2018:484





# **Bayesian Methods for Preventive Maintenance**

Of wind turbines

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## Foreword

**Bayesianska metoder för förebyggande underhåll är ett projekt som är finansierat av Energiforsk och Energimyndigheten genom programmet Vindforsk.**

När väl vindkraftverken är på plats gäller det att säkerställa ett kostnadseffektivt underhåll.

Projektet har tagit fram en metod baserad på Bayesiansk statistik och SCADA-data som på ett säkert sätt kan minska kostnaden för det förebyggande underhållet. Ett praktiskt exempel verifierar också metoden som, när den väl är kommersiell, kan få stor betydelse för vindkraftsindustrin.

Projektet har utförts av Uppsala universitet med Bahri Uzunoglu som projektledare.

Göran Dalén

Ordförande i Vindforsk

Reported here are the results and conclusions from a project in a research program run by Energiforsk. The author / authors are responsible for the content and publication which does not mean that Energiforsk has taken a position.

## Sammanfattning

Projektet utgår från den enkla idén att bedöma den optimala tiden för förebyggande underhåll baserat på tillgänglig information från SCADA-data för vindkraftverk. Tillvägagångssättet är kvantitativt, mätbart och repeterbart. Resultaten hör hemma inom teknik med koppling till tillförlitlighet och säkerhet samt förebyggande underhåll av vindkraftverk. Bayesianska metoder är välkända matematiska och statistiska tillvägagångssätt. Metoderna omfattar en statistisk lärandestrategi som är populär inom drift och underhåll i många sektorer, dock har dess genomslag inom vindområdet varit något långsam och förutsättningar finns för ett växande intresse under kommande år. Det nya i forskningen har här inte bara varit att introducera detta koncept inom vindkraftområdet utan också att introducera subjektiv logik till området samt att införa några nya koncept för datainsamling. Dess genomförande är enkelt för ingenjörer med statistisk bakgrund samtidigt som det är snabbt, enkelt och billigt i jämförelse med många andra metoder.

I projektet har en Bayesiansk uppdateringsstrategi färdigställts och vidareutvecklats. Arbetets förlängning till subjektiva yttranden från vindkraftsparksoperatören eller teknikern har inte blivit genomfört i detta sammanhang tidigare. Subjektiva yttranden om Bayesianska cykler har här framgångsrikt använts samtidigt som experter kan påverka distributionsparametrarna utan kunskap om statistik, endast genom att presentera sina åsikter som tro, misstro eller osäkerhet. Besluten och deras inverkan på de statistiska parametrarna, såsom minimal tid för underhåll och kostnaden för nya strategier kan presenteras direkt för vindkraftsparksägare och tekniker som kvantitativa data samtidigt som deras input och åsikter också är av relevans.

Metoden kompletterar kvantitativa data från SCADA. Det förebyggande underhållet av en vindkraftsanordning som utgör en mycket viktig komponent för turbinfel har undersökts i den här studien som uppvisar metodens genomförbarhet.

## Summary

The context of this research is about the simple idea of assessing the optimal time for preventive maintenance based on available information to us from SCADA data of wind turbines. The approach is quantitative, measurable and repeatable. As a result, the contexts of these results belong in reliability and safety engineering and preventive maintenance of wind turbines. However let's give some more attention to Bayesian terminology in the title. While this is a statistical learning strategy used in every walk of life including operation and maintenance, its penetration into the wind community has been somehow slow which can only attract more interest in the following years. While the novelty of the research has not been only introducing this concept to wind power community but also on introducing subjective logic into this community as well as introducing some new data mining concepts. It has simplicity in its implementation for any engineer with statistics background while its implementation is quick, simple and cheap in comparison to methods that are dependent on model of the specific technology. Bayesian methods are well-known mathematical statistical approaches however its introduction to conservative wind community is under progress.

In more specific terms, an optimal Bayesian update strategy that implements subjective opinion of the experts are introduced for preventive maintenance of wind turbines. The Bayesian update strategy that has been proposed in the project proposal has been completed and developed further. Extension of the borders of our knowledge was pushed beyond the project proposal definition. While using optimal Bayesian adaptive update strategies for optimal preventive maintenance time has been developed in literature "not necessarily for preventive of wind farms" which is addressed here as novelty, extension of this work to subjective opinion of the wind farm manager or technician has also not been implemented in this context in literature before. Herein subjective opinion has been successfully implemented to Bayesian cycles while experts can impact the distribution parameters with no knowledge of statistics but just by presenting their opinion as belief, disbelief or uncertainty. The choices and its impact on the statistical parameters such minimal time of maintenance and cost of new strategy is directly presented to wind farm manager and technician as quantitative data while their input is opinion. The approach complements the quantitative data from turbine SCADA. Preventive maintenance pitch control device of a wind turbine which is a very important component for turbine failures has been investigated in this study that exhibits the feasibility of the approach. The approach has successfully implemented the proposed objectives of Bayesian maintenance of wind turbines but extended the findings to subjective logic and beyond with novelties in several fronts.

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# 1 Introduction/Background

Operation and maintenance strategies for wind farms are at most importance for economical energy production while the wind turbine fleet is increasing in the world with increasing production capacity. Maintenance actions and services for wind turbines are usually provided by manufacturer for normal operations with guarantee agreements. Wind managers who search for better warranty and maintenance contracts would like to assess their situation. Since the manufacturers have financial gains from these contracts and further competition between manufacturers make the information transparency limited in terms of data availability as a natural conditions of the business environment. Wind managers who search for better warranty and maintenance contracts and wind turbine manufacturer can work together in a win-win situation in approaches like this presented in this paper. Herein Bayesian adaptive preventive maintenance strategy is combined with subjective opinion. Sharing of information between owner and manufacturer can be handled at different levels of complexity. In this context one approach that can solve this conflict of interest can be adaptive Bayesian preventive maintenance handled by the manufacturer while subjective opinion strategy managed by wind turbine owner, manager or technicians where the information exchange is managed via the distributions presenting some level of confidentiality.

The maintenance action needed can be at different levels, it might be replacement of the whole sub-system/system named herein as A-type or replacement of part of the sub-system/system by minor repairs named herein as B-type. Age replacement or the block replacement policy will be investigated here with minimal repairs. Barlow and Hunter generalized this approach by expanding minimal repair at failures. The work of has been employed by several researchers. The failure distribution is assumed to be unknown or contains uncertain parameters in general. To estimate distribution parameters accurately will benefit accurate calculation of mean life of the system. This has been addressed in several studies in literature. The approaches presented for Bayesian will be extended to subjective opinion and wind turbines O&M in this study.

Traditional probability theory of aleatory uncertainty is not suitable when probability density functions (PDFs) associated with the probabilistic parameters are not available. For epistemic uncertainty, possibility theory is available, but it is limited to just type of uncertainty. These two theories can be unified as constrained cases of evidence theory with subjective and probabilistic logic. Opinions of subjective logic related to the belief functions of Dempster–Shafer evidence theory. In view of the attractive features of evidence theory with subjective and probabilistic logic, particularly pertinent to operation and maintenance here, the objective of the present research is to assess the system outputs in parameter regimes by an expert. Furthermore, Bayes' theorem provides a method of inverting conditional probabilities in probability calculus and statistics. Subjective logic generalizes probability calculus whereby arguments are represented as opinions that can contain degrees of uncertainty. This paper employs Bayes' theorem in the formalism of subjective logic for operation and maintenance.

The approaches presented here are in statistical in nature so they are not technology dependent since they is applied and can be applied to wide range of technologies including wind turbines however the approach is general enough to take into account the technology dependent methods if needed. There are several computational models such as neural networks, Markov chains which can also be reformulated under the Bayesian concepts however the review of these approaches is beyond the scope of this report while the field is exhaustive however the evolution of Bayesian approaches for preventive is within the scope of this report while the projects is about Bayesian methods. It is important to preventively maintain a system to avoid failures during operation especially when such an event is costly and/or dangerous in this case wind turbines. The objective of the reliability study is on when to maintain the system. The number of failures during actual operation should be optimal and should be reduced to as few as possible by means of maintenance. In most maintenance models, a maintenance action (replacement) regenerates the system. For a complex system the maintenance action is not the replacement of the whole system. It is mostly the repair or replacement of a part of the system. This type of maintenance action will not renew the system. Barlow and Hunter investigated two types of preventive maintenance policy, one type for single-item systems and another for multi-item systems. These two types of policy have been studied extensively in the literature furthermore Nguyen and Murthy, Nakagawa, Sheu and Liou, investigated sequential preventive maintenance policy with the assumption that the life distribution of the system changes after each maintenance cycle.

Replacement policies aim to preventively maintain a system such as the age replacement policy and the block (periodic) replacement policy. Barlow and Hunter introduced the replacement policy by incorporating minimal repairs at failures when the failure distribution of the system is known with certainty. Failure distribution is extensively used in preventive maintenance. The failure distribution of a system is usually unknown or known with uncertain parameters in practice as a result there is a need to select an appropriate estimation method to predict accurately the parameter(s) of a given distribution which was investigated by Gibbons and Vance, Lawless, Mann, Pan and Chen, Sinha and Sloan, Soland, Thoman et al. and Varde. Sathe and Hancock adopted a Bayesian approach by considering prior distributions on the shape and scale parameters of a Weibull failure distribution for an optimal replacement policy. Mazzuchi and Soyer employ the Bayesian decision theoretic approach and develop a Weibull model for both the block replacement protocol with minimal repair and the traditional age replacement protocol. However, the repair cost for system failures may be random and unknown in practice. As exactly proposed in the project proposal, the project investigated these concepts for wind turbines employing Bayesian update strategy. While the novelty of the research has not been only introducing this concept to wind power community but the novelty is also introducing subjective logic into this community as well as introducing some new data mining concepts. It has simplicity in its implementation for any engineer with statistics background while its implementation is quick, simple and cheap compared to other methods that are heavily dependent on technology dependent models.

## 2 Method

First year of the project is conducted for data preprocessing exactly as defined in the project.

- Separated the failures according to the service duration which is Manual Restarts, Minor Repairs Major Repairs has been refined.

In the second year of the project as defined in the project.

- Identified optimal preventive maintenance time, employed Monte Carlo random sampling for preventive maintenance costs. Developed Bayesian update strategy for the wind farm.
- Introduced the subjective opinion of the technician and wind farm owner.
- Test Bayesian strategy for wind farm pitch control device to simulate the optimal maintenance time.

To test these concepts for the wind turbines, the active power control system is an essential component that optimizes efficient use of wind resources with given constraints of safety. This is a typical component for benchmarking. The pitch control system which is a very important part of major wind turbine controls aims to optimize efficiency while acts to operate with safety in bad weather conditions. As in any dynamic component, the pitch control system is subjective to several frequent failures with large residence time relative to other components. Pitch control system for a site in Sweden in cold climate will be investigated in this study. The chosen turbine is a 2MW turbine with rotor diameter 82m. There are three identical wind turbines on the site. The methodology used here has focused on the control system maintenance particularly on the pitch control devices which showed several times failure for the duration of data availability from 2009-01-01 to 2015-10-28 for approximate five years data of this site.

For the preventive maintenance of active pitch control systems based on the findings labor is 480 €. This is based on 60 €/h-man, always considering 2 men and 4 hours. The lubricants are 100 €. Parts and displacement of parts can vary so an approximate figure of 580 € was implemented for the preventive maintenance costs.

For the corrective maintenance of active pitch control systems the average annual electricity price was taken as 0.02924 €/kWh based on Nordpool 2016 annual average. This is for the unavailable kWh production when the turbine was not available at major failure at the end of the life cycle. The maintenance usually consists in replacing the engine of the blade. The cost for engine is taken as 2000 \euro~, sensor placement is taken as 50 €. As man hours 60 €/h-man always considering 2 men are taken into account by trebling the labor of preventive maintenance plus the lubricants so 1540€ plus 2050 € is implemented for the replacement costs.

Three of the turbines with available SCADA data were investigated for duration of observations of the pitch control system that was maintained several times during the operation period. This data was preprocessed to find start and stop of each

failure with duration of each failure processed as presented in Table 1 below in days. The information from three turbines are preprocessed into cycles with each cycle starting with start of SCADA recordings or major failure. Cycle ends with major failure or end of life cycle. Later this data is normalized with duration of maximum cycle days which is 1846 days from the Table 1 below for Bayesian cycles. The life cycle of the pitch control device components are not taken from the manufacturer but based on actual data.

Table 1: Failure times (days) in each cycle for pitch control of identical turbines.

|         |        |        |        |        |        |         |         |
|---------|--------|--------|--------|--------|--------|---------|---------|
| Cycle 1 | 40.22  | 40.30  | 62.98  | 117.06 | 323.93 | 325.086 | 1846.18 |
| Cycle 2 | 316.30 | 667.47 | NaN    | NaN    | NaN    | NaN     | NaN     |
| Cycle 3 | 650.91 | 652.22 | 655.50 | NaN    | NaN    | NaN     | NaN     |

Table 2: Unavailability (*kWh*) in each cycle for pitch control of identical turbines.

|         |         |          |          |       |        |         |          |
|---------|---------|----------|----------|-------|--------|---------|----------|
| Cycle 1 | 1167.50 | 1838.37  | 1764.09  | 11.75 | 473.38 | 1656.04 | 33168.24 |
| Cycle 2 | 300.67  | 82841.68 | NaN      | NaN   | NaN    | NaN     | NaN      |
| Cycle 3 | 59.57   | 2439.27  | 19398.92 | NaN   | NaN    | NaN     | NaN      |

### 3 Results

In order to test the feasibility of the approach, the failure cycles from Table 1 are implemented in the Bayesian approach for updates. The Bayesian approach is updating well-known failure distribution parameters. For mathematical details, please refer to papers. The simulations are tested with availability and without availability data as given in below Table 2. These are discussed in Section 2. If availability data of Table is used, it is added to failure costs coefficients where it is added to existing costs. The worst case of unavailability is taken as representative case. This is for each cycle from Table 2 in failure cost calculations.

The Bayesian simulations for Weibull distribution beta parameter update are presented in Figure 2 for each cycle while more information becomes available with and without availability costs. The information is taken from three turbines with pitch control device failures. It can be clearly observed from Figure 2 that beta distribution is converging low probability disbelief regions of beta coefficients that directly impact the corrective maintenance time forecast by generating more conservative corrective maintenance time in-line with observations.

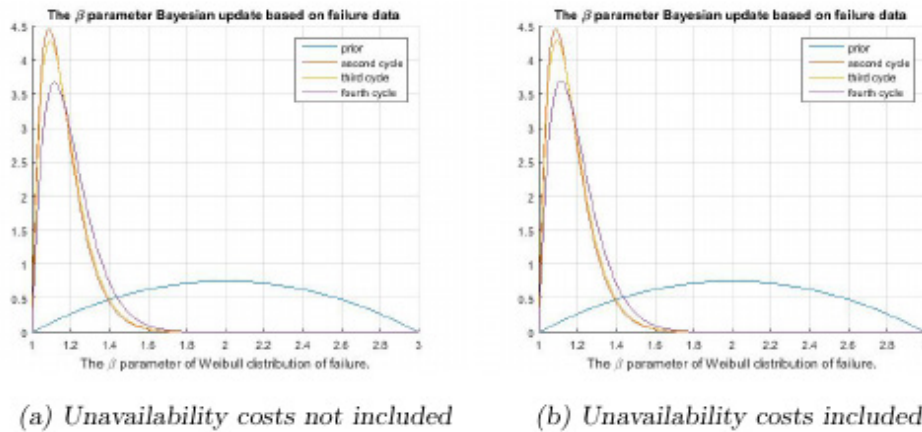


Figure 2: The  $\beta$  distribution after each cycle update from prior to posteriors,  $c_p$  is not random.

The cost function update for each cycle is presented in Figure 3 where the time dependent optimal cost function is presented from 0 to 5 unit time where the normalization was achieved by employing 1846 days as normalization factor. The cost was normalized.

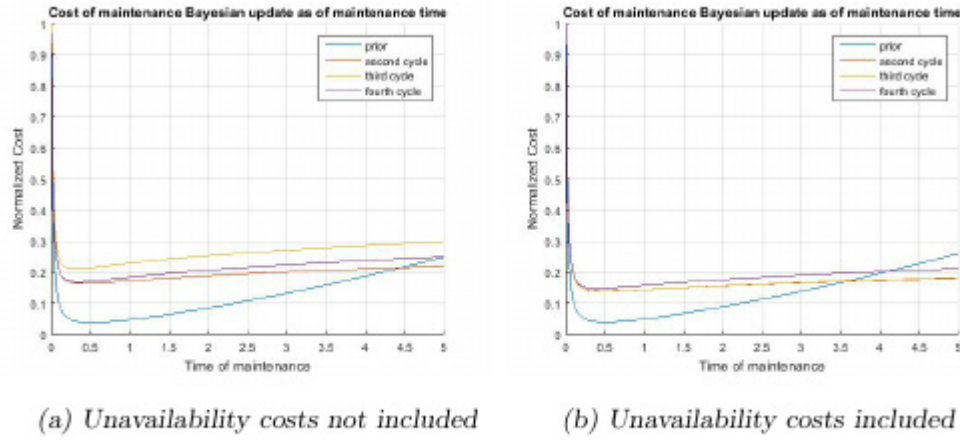


Figure 3: The cost function after each cycle update from prior to posteriors,  $c_p$  is not random.

It can be observed from the Figure 3 that implementing the unavailability costs significantly impacts the optimal time by making it more conservative. These findings are presented in Table 3 while the cost column in Table 3 about subjective opinion of the expert will be discussed below.

Table 3: Optimal time and its costs for all cycles and subjective opinion of expert.

| Cycles                    | Prior (1) | 2      | 3      | 4      | Expert |
|---------------------------|-----------|--------|--------|--------|--------|
| Without unavailability    |           |        |        |        |        |
| Optimal time              | 0.5000    | 0.4900 | 0.4800 | 0.4000 | 0.3800 |
| Optimal time random $c_p$ | 0.5000    | 0.3900 | 0.2000 | 0.1400 | 0.1300 |
| Optimal cost              | 0.0396    | 0.1391 | 0.1383 | 0.1479 | 0.1572 |
| Optimal cost random $c_p$ | 0.0426    | 0.1440 | 0.1320 | 0.1434 | 0.1599 |
| With unavailability       |           |        |        |        |        |
| Optimal time              | 0.5000    | 0.4100 | 0.3100 | 0.3400 | 0.3100 |
| Optimal time random $c_p$ | 0.5000    | 0.3700 | 0.1500 | 0.0800 | 0.0700 |
| Optimal cost              | 0.0379    | 0.1640 | 0.2105 | 0.1686 | 0.1843 |
| Optimal cost random $c_p$ | 0.0426    | 0.1811 | 0.2121 | 0.1535 | 0.1727 |

As can be observed from Table 3, the optimal time for preventive maintenance follow the trend in data presented in Table 1 and Table 2. Random preventive costs gives the most conservative results since the probability of the preventive maintenance coming as maximum is low if the results at the preventive maintenance cost mean is based on normal distribution so Monte Carlo sampling simulates more conservative results. Hence the algorithm changes strategy since the cost of preventive maintenance is low.

The belief, disbelief and uncertainty for each of the cycle 4 results of Bayesian adaptive approach are presented in Table 4 as binomial opinion in the barycentric triangle coordinates of binomial opinion.

Table 4: Quantitative values of opinion presented to expert after Bayesian cycle 4.

|                         | Belief | Disbelief | Uncertainty | Baserate | W      |
|-------------------------|--------|-----------|-------------|----------|--------|
| Without unavailability  |        |           |             |          |        |
| Opinion                 | 0.0503 | 0.8549    | 0.0948      | 0.5000   | 2.0000 |
| Opinion (random $c_p$ ) | 0.0515 | 0.8545    | 0.0940      | 0.5000   | 2.0000 |
| With unavailability     |        |           |             |          |        |
| Opinion                 | 0.0513 | 0.8542    | 0.0944      | 0.5000   | 2.0000 |
| Opinion (random $c_p$ ) | 0.0429 | 0.8732    | 0.0839      | 0.5000   | 2.0000 |

Bayesian results from the fourth cycle for the case without unavailability costs are introduced in Table 3 and this is presented in Figure 4.

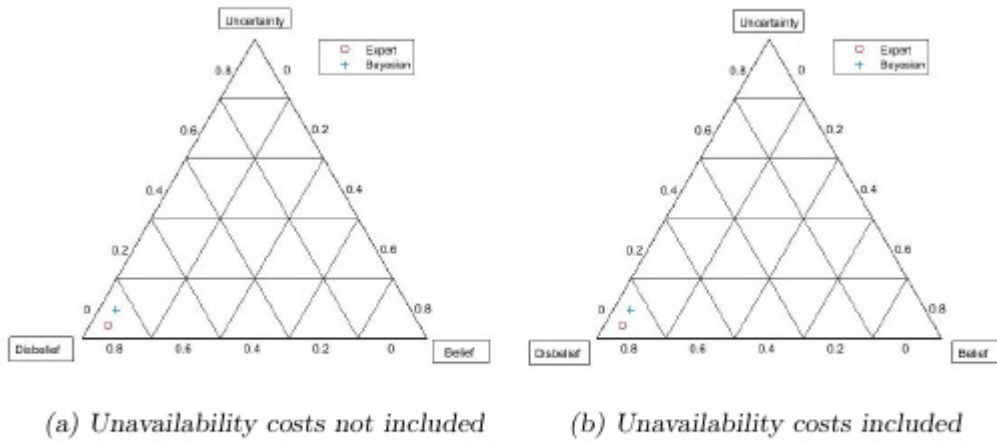


Figure 4: Subjective opinion on a barycentric coordinate system with the expert opinion marked in circle.

Once the expert decides to introduce 0.05 more disbelief and 0.05 less uncertainty, it marks the circle in visual aid of ternary plot of Figure 4. The **beta** distribution is impacted as in Figure 5 while **mu** and **nu** parameters of the **beta** distribution are impacted when more disbelief and less uncertainty is introduced. For this example, the distribution moves to left consistent with the opinions.



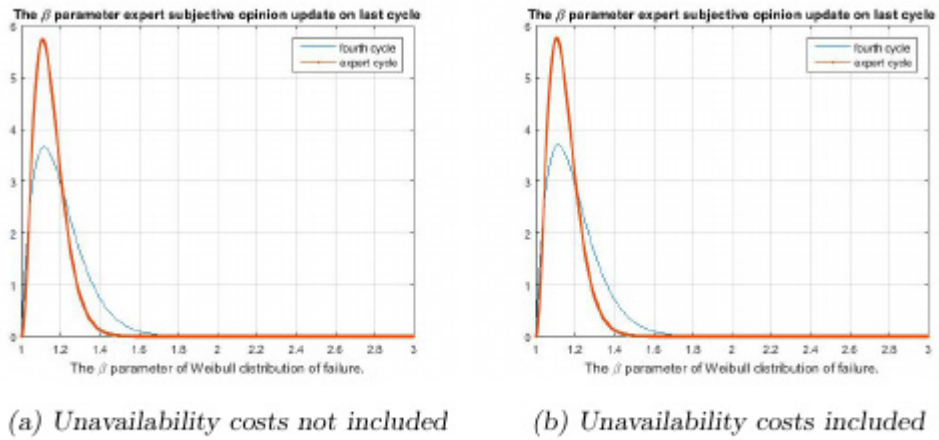


Figure 5: Subjective opinion of the expert impact on the last cycle of the  $\beta$  distribution.

The impact of the expert opinion on the cost functions are introduced in Figure 6. The findings based on these simulations for expert opinion on costs and optimal times were presented in Table 3 at the expert column where the more conservative opinion of the expert is presented.



## 4 List of publications

**Publication 1:** An earlier study as a continuation of the work that has started earlier to approval date of project has been published <http://digital-library.theiet.org/content/journals/10.1049/iet-rpg.2015.0020> . A poster presentation was made at Windpower in focus conference.

**Publication 2:** “Data Mining via Association Rules for Power Ramps Detected by Clustering or Optimization” by Nurseda Yildirim and Bahri Uzunoglu Transactions on Computational Science XXVIII, Volume 9590 of the series Lecture Notes in Computer Science pp 163-176 doi: [http://dx.doi.org/10.1007/978-3-662-53090-0\\_9](http://dx.doi.org/10.1007/978-3-662-53090-0_9)

**Publication 3:** “A Bayesian approach with subjective logic for adaptive preventive maintenance of wind turbines” Bahri Uzunoglu : under review <http://dx.doi.org/10.13140/RG.2.2.35383.52647> at Reliability Engineering and System Safety

**Publication 4:**“ Locating distribution power system fault employing Bayes theorem with subjective logic” Bahri Uzunoglu International Conference on System Reliability and Safety, ICSRS on. IEEE

**Publication 5:**“ An adaptive Bayesian approach with subjective opinions for preventive maintenance” The Science of Making Torque from Wind (TORQUE 2018), Physics conference series. (Early acceptance

## 5 Discussion

A Bayesian adaptive preventive maintenance strategy that can address the opinions of the expert has been introduced. This approach can successfully address the expert opinions in the context of the quantitative data for wind turbine maintenance while statistical knowledge from the expert is not expected. The expert can mark their opinion in visual aid to be used for statistical cycles. However the knowledge of the expert in addition existing data can be employed for further prediction cycles once more data becomes available for further analysis. The approach can be extended to several expert opinions. Bayesian preventive update strategy has been implemented for wind turbine pitch control device maintenance data. The approach is not exclusive and can be applied to any preventive maintenance data for optimal maintenance time prediction with expert opinion. . It has simplicity in its implementation for any engineer with statistics background while its implementation is quick, simple and cheap in comparison to methods that are dependent on model of the specific technology.

There were several discussions with colleagues and companies during the duration of this project with Energimyndigheten, Vindforsk, Energiforsk, Kim Emil Andersen Vestas, Breeze, Simis, Christos Kaidis, Solute and others. Some of these companies have presented clear interest and support with letters for further development of these ideas.



# BAYESIAN METHODS FOR PREVENTIVE MAINTENANCE

The context of this research is about the simple idea of assessing the optimal time for preventive maintenance based on available information to us from SCADA data of wind turbines. The approach is quantitative, measurable and repeatable. As a result, the contexts of these results belong in reliability and safety engineering and preventive maintenance of wind turbines.

Maintenance of wind farms can be systematically categorized as preventive, corrective, and condition based maintenance. Most of the major the operation and maintenance costs are dominated by corrective maintenance. To reduce these costs it is necessary to lower the amount of corrective maintenance uncertainty.

To reduce the operation and maintenance costs it is necessary to lower the amount of corrective maintenance by shifting some parts of strategy to preventive maintenance which is achieved in this project by employing Bayesian adaptive approaches that employs newly arrived data to update predictions. The approach has simplicity in its implementation for any engineer with statistics background while its implementation is quick, simple and cheap in comparison to methods that are dependent on model of the specific technology.

Energiforsk is the Swedish Energy Research Centre – an industrially owned body dedicated to meeting the common energy challenges faced by industries, authorities and society. Our vision is to be hub of Swedish energy research and our mission is to make the world of energy smarter! Vindforsk is operated in cooperation with the Swedish Energy Agency.