ZAGADNIENIA
EKSPLOATACJI
MASZYN
Zeszyt 3 (151) 2007

A. HJORTELAND[*], T. AVEN[*]

On how to use expert judgments in regularity analyses to obtain good predictions

K e y w o r d s

Regularity, uncertainty, observable quantities, expert judgements.

S ł o w a k l u c z o w e

Regularność, niepewność, wielkości obserwowalne, opinie ekspertów.

S u m m a r y

The purpose of regularity analysis is to assess future deliveries of production and transportation systems, such as oil and gas installations. When conducting such analysis, models are developed reflecting the performance of various equipment, for example compressors and pumps. To assess the equipment performance there is a need for relevant knowledge, including observed data and expert judgments.

One of the challenges in regularity analyses is to assess uncertainties for the large number of quantities in the models being used. These quantities are either, observable quantities such as lifetimes or repair times, or statistical expected values or probabilities, such as MTTF or MTTR. The purpose of this paper is to present and discuss a practical approach for such assessments using the combination of expert judgements and hard data. The approach is based on a Bayesian framework, with focus on prediction and uncertainty assessments of observable quantities.

1. Introduction

Regularity is a term used to describe how a system, for example an offshore oil and gas production and transport system, is capable of meeting demands for deliveries or performance. Production availability, deliverability or other measures can be used to express regularity. In regularity analyses these measures are

[*] Statoil ASA, 4035 Stavanger, Norway, tel. (+47) 480-80-159, e-mail: atle.hjorteland@statoil.com.

assessed, and in this way the analyses support decision-making in design and operation.

Suppose that a regularity analysis is to be conducted for a gas producing offshore installation during the concept development phase. The quantities of interest are regularity measures such as gas production within a certain period of time, and to be able to predict such quantities, information is gathered to increase the knowledge about the production process. A model, reflecting the process is developed, and available information is used to express uncertainty related to the outcome of the unknown quantities in the model. The information used can be categorised as:

1. Historical (observed) data.
2. Expert judgements.

One of the challenges in regularity analyses is to assess uncertainty for a very large number of quantities. The planned offshore installations main functions are to receive rich gas from the reservoir, separation of gas and fluids, gas compression and gas export to an onshore process plant. Each of these functions contains a large number of subsystems and the subsystems contain equipment like pumps, valves, pipes and vessels. A model is developed linking the performance of the equipment. When considering the performance of equipment, quantities such as uptimes and downtimes are included. The remaining part of the regularity analysis is to assess uncertainties about the equipments future performance. When predicting regularity of such a system, it is normal that there are approximately 600–800 unknown quantities in the model. Clearly, assessing such large numbers of quantities can be very resource demanding.

Hence there is a need for procedures that give guidance on how to perform the uncertainty assessments. Some guidance is given by the industrial standard for regularity management and reliability technology, cf. Norwegian Technology Standard Institution [1], which provides requirements and guidelines for planning, execution and use of regularity analyses and management. The above-presented approach to regularity analyses is based on this standard. The standard adopts a predictive, Bayesian approach to regularity in the sense that focus is on predicting observable quantities and probability is used as a measure of uncertainty, seen through the eyes of the assessors, cf. Aven [2]. However, this standard does not give detailed recommendations on how to deal with the many challenges related to uncertainty assessments, such as:

- The vast number of quantities to be assessed.
- Lack of sufficient amount of relevant hard data.
- How to incorporate expert judgments.

This paper addresses these challenges in the context of the predictive, Bayesian approach. More specifically we look at ways of compensating for lack of sufficient amount of relevant hard data, by using expert judgments. In a Bayesian context the normal procedure would be to use probability models for the uptimes and downtimes of the equipment, and specify uncertainty distributions for the parameters of these probability models. Bayesian statistics is mainly concerned about inference on parameters in probability models. Based on thought experiments, i.e. introducing 'similar' situations, the traditional Bayesian approach gives focus on fictional parameters. This means that the analyst is to express uncertainty related to an unobservable fictional quantity based on a sequence of hypothetical similar situations.

Such a full Bayesian procedure is however difficult to carry out in practice, and in this paper we discuss the use of expert judgments as a tool for simplifying this procedure. We discuss how expert judgment can be used to establish suitable uptime and downtime distributions, and avoid the problem of dependencies between consecutive uptimes (downtimes), by strengthening the background information for the uncertainty assessments. Adopting a Bayesian approach the consecutive uptimes (downtimes) are dependent as we learn by observing the uptimes (downtimes). However, it turns out that if the background information is sufficient strong, for example obtained by using expert judgments, this learning process can be ignored. The result is that we may use identical distributed, independent distributions for the uptimes (downtimes). This simplifies the analysis to large extent.

The literature presents a number of methods for uncertainty assessments utilizing expert judgments. However, most of these methods are somewhat technical and complex for application in regularity analyses. The regularity analyst will in most cases have problems when applying these procedures, concerning both technicality and the demand of resources. For the purpose of the regularity analysis there is a need for a simple approach, which can be used in an operational setting. In this paper we discuss the structure of such an approach, again in the context of the predictive, Bayesian framework. The starting points are the requirements and guidelines given by the industrial standard for regularity management and reliability technology [1], and expert judgment elicitation methodology as presented by Cooke [3] and others.

The rest of this paper is organised as follows: In Section 2 we formalise the challenges described above using a regularity analysis example as a starting point, emphasising the problems of dependencies. In Section 4 we give some remarks on the expert judgement elicitation process.

2. A regularity analysis example

Again we refer to the planning of the gas producing offshore installation. A regularity analysis is carried out during the concept development phase, supporting assessments of future gas deliveries and company profit. As a basis for such assessments, there is a need for information about key performance measures, both technical measures (related to equipment properties, system capability, future production, etc.) and financial measures (related to future exchange rate, planned and actual investments, expense budget due to equipment repair and maintenance, etc.). In this paper emphasis is put on the regularity analysis and prediction of gas production.

The main process stages of the gas producing offshore installation are illustrated in Figure 1.

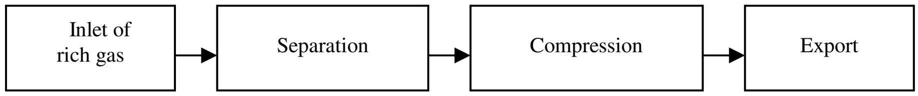

Fig. 1. Illustration of the system's main process stages
Fig. 1. Graficzna prezentacja głównych etapów systemu

Let Y_t denote total production for the relevant period of time [0, t], for example a specific one-year period. The quantity Y_t can be expressed in cubic meter of gas or normalized as a percentage in relation to the demand volume.

Now in the planning phase Y_t is unknown, thus we are led to prediction of this quantity. Later we can accurately measure Y_t; Y_t is what we refer to as an observable quantity. The prediction can be done in different ways. We may compare with similar systems if available, or we could develop a more detailed model of the system reflecting the various equipment of the concept of interest, i.e. a regularity model. Using such a model, we try to reduce the complexity of the uncertainty related to Y_t, and thus reduce uncertainty.

But there are still some uncertainties remaining, related to the times to failure and the duration of downtimes of the various equipment included in the process stages. These are the unknown quantities of the model. By assigning probabilities related to their possible outcomes, we will arrive at an uncertainty distribution and prediction of Y_t.

To see in more detail what the basic elements of this framework are, we below present the details of such a regularity model. The presentation is based on the assumption that the system is a binary system of binary components.

Let $X_t(i)$ represent the state of equipment i, i = 1, 2, …, n; $X_t(i) = 1$ if component i is functioning at time t and $X_t(i) = 0$ if component i is not functioning at time t. We assume $X_0(i) = 1$. Let T_{im}, m = 1, 2,…, represent the positive length of the mth operation period of component i, and let R_{im}, m = 1, 2, …, represent the positive length of the mth repair time for component i. An overview of the unknown quantities is listed Table 1.

Furthermore, let g denote the relationship between Y_t and the uptimes and downtimes T_{im} and R_{im}. It is clear that Y_t can be determined from the uptimes and downtimes – an explicit formula is given in Aven and Jensen [4], p. 101, and thus we can write

$$Y_t = g(t, T, R), \tag{1}$$

where: T and R are the vectors of T_{im} and R_{im}.

Table 1. The unknown quantities of the regularity model

Process stages	Equip. (i)	Time to failure (T_{im}, m = 1, 2, …)			Time to repair (R_{im}, m = 1, 2, …)		
		T_{i1}	T_{i2}	…	R_{i1}	R_{i2}	…
Inlet of rich gas	1	T_{11}	T_{12}	…	R_{11}	R_{12}	…
	2	T_{21}	T_{22}	…	R_{21}	R_{22}	…
	…	…	…	…	…	…	…
Separation	…	…	…	…	…	…	…
Compression	…	…	…	…	…	…	…
Export	…	…	…	…	…	…	…
	n-1	$T_{(n-1)1}$	$T_{(n-1)2}$	…	$R_{(n-1)1}$	$R_{(n-1)2}$	…
	n	T_{n1}	T_{n2}	…	R_{n1}	R_{n2}	…

The function g is a model. If all the uptimes and downtimes T_{im} and R_{im} were known, Y_t, could be predicted with certainty, given the assumptions of g. However, in practice, such information is not available, and uncertainties have to be taken into account.

Now, how should we assess the uncertainties of the vectors (T, R)? Ideally, a simultaneous distribution for all lifetimes and repair times should be provided, but this is not feasible in practice. Clearly, if we could use independence between all the quantities, the uncertainty assessments would be manageable, as we could assign a probability distribution for each quantity, and if we could apply the same distribution for the uptimes and the same distribution for downtimes, we are more or less done. However, we do not have independence and identically distributed quantities. Think of the time development process for one component, from time 0 to t. Having observed the four previous lifetimes (say), we have learnt about the component performance and should take this into account when assigning the probability distribution for the fifth lifetime.

The Bayesian solution to this problem is to introduce probability models, cf. e.g. Bedford & Cooke [5] and Bernardo & Smith [6]. By conditioning on the parameters of these models, independence is obtained. Unconditionally, the random quantities are exchangeable, and not independent, but the probability models categories the components according to specific properties, and given these properties, the components may be considered independent.

As an example, an exponential distribution with parameter λ could be utilized to express uncertainty related to T_{im}. Here λ is interpreted as the long run fraction of failures when considering an infinite (or very large) number of 'similar' situations to the one analyzed. The parameter λ is unknown; it is a random quantity, and the assessors uncertainty related to its value is specified through a prior (posterior) distribution H (λ). Given λ, the lifetimes are independent and exponentially distributed with parameter λ.

From this set-up, we can calculate the distribution of Y_t, using standard probability calculus. However, running a full Bayesian analysis according to this scheme is challenging since we have to specify a high number of prior (posterior) distribution. Experience from regularity analyses applications shows that there is a need for simplifications to obtain a more practical tool. And the natural first choice for such a simplification is to question the need for assessing uncertainties of the parameters. Is it possible to justify the use of fixed parameters? Is it possible to justify independence between the random quantities?

According to the Bayesian theory, ignoring the uncertainty about λ gives misleading over precise inference statements about X, cf. e.g. Bernardo & Smith [6], p. 483. This reasoning is of course valid if we work within the standard Bayesian setting, considering an infinite number of exchangeable random quantities. However, if our focus are the observable quantities of the time interval considered, and we have a sufficient strong background information for assessing the uncertainties, the additional information gained by observing some lifetimes (repair times) are not significant, in the sense that we need not adjust the uncertainty distribution for the remaining lifetimes (repair times).

Thus, as a simplification of the uncertainty assessments, we could judge all T_{im} and R_{im} to be independent and use the same distribution F for all lifetimes and the same distribution G for all repair times for a given type of equipment.

The requirement of having strong background information is of course not always met. But the point made in this paper is that sufficient knowledge may be obtained by using expert judgments in some cases. Adding information by using expert judgment is the key to ensure independence. The result is that we may use, for selected components, identical distributed, independent distributions for the uptimes and downtimes. This simplifies the analysis to large extent.

3. Uusing expert judgment to justify independence

We return to the analysis in the previous section. The system being analyzed is in the concept development phase, and has therefore never been observed in operation. This means that no specific historical data of performance exists, either on system or on equipment level. However, similar equipment will in most cases have been observed on comparable installations and in comparable operational environment. This means that some generic observed data are normally available. In addition to generic data, some information from design, fabrication and testing of equipment will in most cases be available.

As an example, generic performance of a compressor can illustrate the collection of historical data. The equipment of interest is a centrifugal, turbine driven, compressor (8000 kW). In this case, the database OREDA [7], provides experience data from 10 compressors, operated on four different installations.

From the observed failures, the mean failure rate is 72 (per 10^6 hours). OREDA [7] also provide an upper and a lower failure rate, with an adjusted factor of ±3.

Now returning to the regularity analysis for the compressor in the concept development phase, and say that we for the first lifetime of the compressor use an exponential distribution with parameter $\lambda = 72$ (per 10^6 hours). For the next lifetime, we should incorporate the information gained by observing this first lifetime, but given that the background information is strong, this is not required, as the 'error' introduced by this simplification is marginal. Thus we use the same distribution also for the second lifetime, and the two lifetimes are considered unconditionally independent. Using the same type of reasoning, we can do the same for the third lifetime and so on.

The difference by applying this approach as opposed to the traditional Bayesian framework would be insignificant in most practical cases. This is demonstrated by the example in Figure 2, where uncertainty related to the 10^{th} time to failure of the compressor is expressed both by assuming unconditionally independence and utilizing the traditional Bayesian approach. When applying the traditional Bayesian approach, the random quantity T_{10} is assumed to follow an exponential distribution given the parameter λ. To express uncertainty related to what will be the true value of λ, a probability distribution needs to be assigned. In this case, a triangular distribution is judged to express the analysts' uncertainty of λ, utilizing the mean, upper and lower failure rate from OREDA [7]. For the exemplification in Figure 2 the 10^{th} time to failure for the compressor is assessed. Monte Carlo simulation is utilized to establish the uncertainty distributions.

From Figure 2, we see that the introduced 'error' when assuming independence is negligible, considering future performance in the concept development phase. The key factor influencing the 'error' is the amount of knowledge. In general there is more information available in the later project phases, and thus the 'error' will decrease.

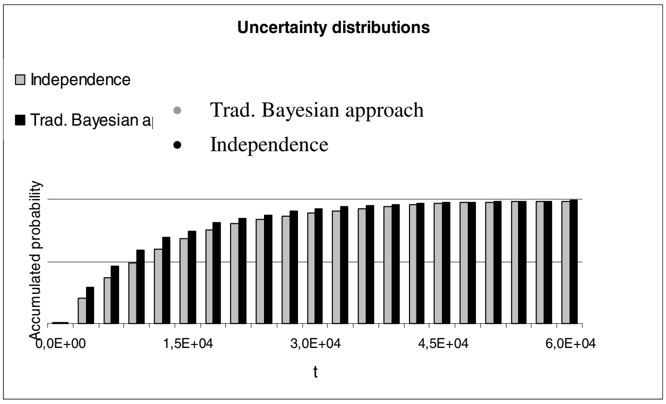

Fig. 2. Uncertainty related to T_{10}, Example 1
Rys. 1. Niewpeność w odniesieniu do T_{10}, przykład 1

If the generic data for the specific equipment provide ‘sufficient knowledge’, i.e. the ‘error’ is judged to be insignificant; an additional observation would have negligible influence on the assessed uncertainties. This means that we could justify the use of unconditional independence. Generic data will often provide sufficient knowledge, but are in some cases limited, regarding quantity and quality/ relevance. The two key factors that have an impact on the relevance of the generic data are technology and application. In general, if the equipment being used is based on new technology or the application of the equipment is new, making use of expert judgments are needed to compensate for limited data.

To illustrate the increased difference between applying independence and the traditional Bayesian framework when having only partially relevant data, we refer to a population of electrical driven compressors with a wide upper and lower failure rate, an adjusted factor of ±10. The reason for the wide boundaries is that this population of compressors is represented by a number of somewhat different models operated in different applications. Clearly, when a population is defined by equipment with varying properties, the historical observations are less relevant and contain more variance. Basically, this means that we become more uncertain when predicting the vectors (T, R).

As an example, an exponential distribution with parameter λ is utilized to express uncertainty related to T_{10}. Analogous to the example in Figure 2, uncertainty of λ, when applying the traditional Bayesian approach, is expressed by a triangular distribution, now with boundaries given by the adjusted factor of ±10. The uncertainty distributions are illustrated in Figure 3. The uncertainty distribution assuming independence remains the same as in the previous example, but the uncertainty distribution in accordance with the traditional Bayesian approach becomes wider as the uncertainty distributions are wider.

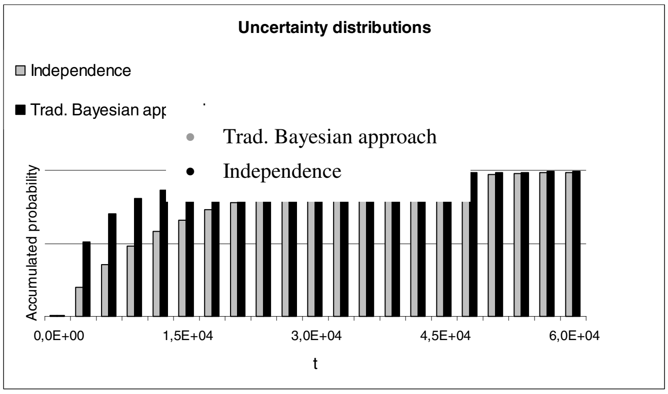

Fig. 3. Uncertainty related to T_{10}, Example 2

As expected the differences between the two distributions are larger in Figure 3 than in Figure 2. The more uncertain the analyst is about a given parameter, the more 'error' is introduced. In most regularity analyses there are stronger information than assumed in Example 2, but there are cases where the background information is poor and then the difference becomes significant. The question is then how to obtain sufficient knowledge.

Sufficient knowledge is a judged amount of knowledge, when the assessor can ignore the assessment 'error'. This point of reference is dependent on the objective of the analysis conducted and relates to the requirements to uncertainty in the various project development phases; cf. Hjorteland, Aven & Østebø [8]. In the concept development phase, the requirement is predictions with a ±30% accuracy, whereas this requirement is ±20% in the detailed engineering phase.

Assume that the generic data from the electrical driven compressors, with an adjusted failure rate factor of ±10, where judged not sufficient by the assessor. This situation leaves the assessor with two alternatives; to apply the traditional Bayesian framework or to establish additional knowledge to ensure unconditional independence. In the following we focus on the latter case, where sufficient knowledge may be obtained by using expert judgments.

When predicting the vectors (T, R) the challenges are to extract the experts' uncertainties related to the future outcome and to combine it with the generic data. The overall assessment process is illustrated in Figure 4. In the following section these challenges are discussed and recommendations are given on how to execute the expert elicitation process from a practical point of view. By conducting the expert judgment elicitation process, independence is ensured.

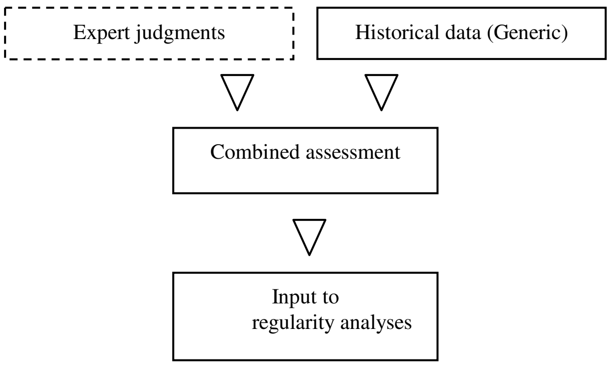

Fig. 4. Main tasks of the assessments of quantities, utilizing expert judgments
Rys. 4. Główne zadanie oceny wartości przy zastosowaniu ocen eksperta

4. Some remarks on the expert judgment elicitation process

The expert judgment elicitation process is a very resource demanding procedure if we are to assign probabilities expressing uncertainty for all the unknown quantities of the regularity model. Expert elicitation is very time demanding and expensive to carry out. The point is that if we treat all T_{im} and R_{im} to be dependent, the expert judgment process would in most cases not be practical feasible. Using the same reasoning as in the previous sections, given that the expert judgments provide sufficient knowledge, the quantities of (T, R) are supposed to be unconditional independent.

Referring to the compressor example in Section 3, Example 2, with an adjusted failure rate factor of ±10, the objective of the elicitation process is to establish an uncertainty distribution with a lower adjusted factor, when combined with generic data. Reasonable resources are to be utilized to gather sufficient knowledge through expert judgments.

The challenge of the elicitation process is to extract the experts' uncertainties related to the future outcomes of the performance measures, i.e. T_{im} and R_{im}. Such quantities are not to be interpreted as MTTF (Mean Time To Failure) and MTTR (Mean Time To Repair), but as future performance measured by T_{im} and R_{im} with a random selected m, given an equipment i. The selected panel of experts is to express uncertainty related to the performance of the relevant equipment, i.e. equipment judge to have an insufficient historical record.

The rest of this Section 4 will concentrate on how to establish uncertainty distributions for the future quantities of (T, R), based on historical data adjusted by experts. A practical, cost-effective approach to the assessment process is sought. The basis for the following discussions is mainly Cooke [3], where basic methodologies for expert judgment elicitation processes can be found.

The following sections contain some discussions related to the two key challenges of the uncertainty assessment process:
– How to capture an experts' uncertainty.
– How to establish the final combined uncertainty distribution.

4.1. How to capture an experts' uncertainty

To communicate the experts' belief about the outcome of an observable quantity, for example the 10^{th} operational period from Example 2, Section 3, a probability distribution is to be established through the elicitation process. This means that the regularity analysts' main challenge is to transform the experts' opinions into a probability distribution.

There are many ways of extracting an experts' opinion based on the notion of probabilities. Most people have poor intuitions regarding numerical probabilities. However, with some training in the terms and concepts of probability assignments, direct elicitation methods may be utilized. The analyst simply asks for the experts' opinion expressed in terms of probability. Clearly, training in numerical probability communication is required when extracting expert opinions, in which the analyst has confidence. The direct elicitation methods are normally supported by points of references, c.f. Lindley [10]. The idea is that the sought probabilities are assigned by comparing with other events, to which probabilities may easily be assigned.

To derive at one particular probability distribution, reflecting the experts' uncertainty, the normal procedure is to use parametric elicitation, cf. Cooke [3]. The parameters of the distribution are determined by specifying some peak value of the distribution and/or quantiles. To be more specific, and as an example, we again consider the 10^{th} operational period from Example 2, Section 3. A probability distribution is to be established through the elicitation process utilizing the exponential distribution. This method presupposes that the experts' uncertainty is in reasonable accordance with this probability class. The experts are asked to predict the percentage k of the 10 lifetimes, having values exceeding x hours. From this we easily compute the mean of the exponential distribution, using the equation:

$$100\exp\{-x/MTTF\} = k \qquad (2)$$

We refer to Cooke [3], De Finetti [11], Lindley [10] and Ramsey [12] for other approaches and examples on how to perform the assignments.

4.2. How to establish the final combined uncertainty distribution

The final combined uncertainty distribution is not a distribution determined by the experts or the historical data, but uncertainty expressed by the analyst. However, the distribution is based on the expert judgements and the historical data. Clearly, the analyst must relate to all the information, consider its relevance and express uncertainty reflecting the available knowledge. The analyst has to combine information. How should this be done in a reasonable practical way?

The process is twofold, considering the opinions from the various selected experts and the observed data:

– Combining the various expert judgments.
– Combining the experts' opinion with the generic data.

Clearly, the experts' beliefs may conflict to a certain extent and the challenge for the analyst is to relate to the various statements within the panel of experts. Formal procedures exist for weighting expert judgments, but such procedures are difficult to carry out in practice. In addition, some would argue that any weighting procedure is inappropriate as all experts appointed should be given the same status, cf. Cooke [3].

For an extensive review of literature concerning weighting procedures and combining expert opinions in general, see Cooke [3].

As an alternative, expert panels are established with the aim of obtaining consensus. The aim is to obtain consensus among the experts and derive at one distribution reflecting the groups' judgments. This is cost-effective and practical applicable approach, but it does not function well if not properly managed.

Building consensus is of major concern when using expert judgements. Five principles are often highlighted, cf. Cooke [3]:

1. *Reproducibility*. It must be possible to reproduce all calculations.
2. *Accountability.* The basis for the probabilities assigned must be identified.
3. *Empirical control.* The probability assignments must in principle be susceptible to empirical control.
4. *Neutrality.* The methods for combining or evaluating expert opinion should encourage experts to state their true opinion.
5. *Fairness*. All experts are treated equally, prior to processing the results of observations.

We find these principles appropriate, except for 'empirical control'. A probability expressing uncertainty cannot be verified when adopting subjective probabilities. Verification of a probability indicates that there exists a true objective probability, which is not in accordance with our interpretation of probabilities, cf. Aven [2] and Hjorteland & Aven [9].

The hard data may be a part of the information given to the expert panel, and then the panel way produces the relevant distributions for the analysts. However, it is also possible that the experts give their assessments without reference to the hard data. The analyst must then combine these two sources of information. This can be done in several ways, for example using a weighting procedure, reflecting the analysts' judgments of the goodness of the information. An example of such a weighting procedure is shown in Table 2, where the goodness is categorised in three levels. Hence if the expert judgments are given the highest score, whereas the historical data the lowest, the weight distribution should be 80% on the expert panel and 20% on the hard data.

Table 2. Weighting system, E%-H%

E%-H%		Expert judgements (E)		
		1*	2*	3*
Historical data (H)	1*	50%-50%	60%-40%	80%-20%
	2*	40%-60%	50%-50%	60%-40%
	3*	20%-80%	40%-60%	50%-50%

* Here 1, 2 and 3 represent the judged goodness of the information.

Praca wpłynęła di Redakcji 24.03.2006 r.

5. References

[1] Norwegian Technology Standard Institution 1998, NORSOK Z-016 Regularity management & reliability technology, Rev. 1.
[2] Aven, T. 2003. Foundations of Risk Analysis – A Knowledge and Decision-oriented Perspective. New York, John Wiley & Sons Ltd.
[3] Cooke, R.M. 1991. Experts in uncertainty. New York: Oxford University Press.
[4] Aven, T. & Jensen, U. 1999. Stochastic Models in Reliability. New York: Springer.
[5] Bedford, T. & Cooke, R.M. 2001. Probabilistic Risk analysis: Foundations and Methods. Cambridge: Cambridge University Press.
[6] Bernardo, J.M. & Smith, A., Bayesian Theory. Chichester: Wiley & Sons, 1994.
[7] OREDA 2002. Offshore Reliability Data, 4th Edition. OREDA Participants.
[8] Hjorteland, A., Aven, T. & Østebø, R. 2004. On how to treat uncertainty in regularity analyses. Submitted for publication in Reliability Engineering and System Safety.
[9] Aven, T. & Hjorteland, A. 2003. A predictive Bayesian approach to multistate reliability analysis. International Journal of Reliability, Quality and Safety Engineering, Vol. 10, No. 3, 221–234.
[10] Lindley, D. 1970. Introduction to Probability and Statistics from a Bayesian Viewpoint, Cambridge University Press, Cambridge.
[11] De Finetti, B. 1974. English translation, Studies in Subjective Probability, Wiley, New York (Original, 1937).
[12] Ramsey, F. 1931. 'Truth and Probability', in Braithwaite (ed.), The Foundations of Mathematics, Kegan Paul, London.
[13] Hjorteland, A. & Aven, T. 2003. Reliability analyses and observables. The 14th European Safety and Reliability Conference (ESREL 2003), vol. 1, ISBN 90 5809 551 7.

W jaki sposób posługiwać się opiniami ekspertów w analizach regularności dostaw w celu uzyskania rzetelnych prognoz

Streszczenie

Celem analiz regularności jest oszacowanie wielkości przyszłych dostaw surowców za pomocą systemów produkcyjnych i transportowych, takich jak instalacje naftowe i gazowe. Przeprowadzając taką analizę buduje się modele opisujące działanie różnorodnego wyposażenia, np. sprężarek lub pomp. Aby cenić pewność działania wyposażenia technicznego niezbędna jest odpowiednia wiedza, obejmująca zaobserwowane i opinie ekspertów.

Jednym z wyzwań w analizach regularności jest oszacowanie niepewności w warunkach dużej liczby elementów składowych w zastosowanych modelach. Te elementy składowe mogą być wielkościami obserwowalnymi, takimi jak czas do uszkodzenia lub czas naprawy, mogą być też wielkościami statystycznymi, wyrażonymi jako wartości oczekiwane, bądź prawdopodobieństwa, na przykład MTTF (średni czas do uszkodzenia) lub MTTR (średni czas naprawy).

Celem niniejszego artykułu jest przedstawienie i przedyskutowanie praktycznych sposobów dokonywania takich analiz w oparciu o kombinację opinii eksperckich i twardych danych. Proponowane podejście oparte jest na modelu Bayesowskim, przy czym skupiono się na predykcji i ocenie niepewności dla wielkości obserwowalnych.