A Bayes-competing risk model for the use of expert judgement in reliability estimation
Coolen, F.P.A.; Mertens, P.R.; Newby, M.J.

Published: 01/01/1990

Document Version
Publisher’s PDF, also known as Version of Record (includes final page, issue and volume numbers)

Please check the document version of this publication:
• A submitted manuscript is the author’s version of the article upon submission and before peer-review. There can be important differences between the submitted version and the official published version of record. People interested in the research are advised to contact the author for the final version of the publication, or visit the DOI to the publisher’s website.
• The final author version and the galley proof are versions of the publication after peer review.
• The final published version features the final layout of the paper including the volume, issue and page numbers.

Link to publication

Citation for published version (APA):

General rights
Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

• Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
• You may not further distribute the material or use it for any profit-making activity or commercial gain
• You may freely distribute the URL identifying the publication in the public portal

Take down policy
If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

Download date: 07. Dec. 2018
Memorandum COSOR 90-32

A Bayes-Competing Risk Model for
the Use of Expert Judgment in
Reliability Estimation

F.P.A. Coolen
P.R. Mertens
M.J. Newby

Eindhoven University of Technology
Department of Mathematics and Computing Science
P.O. Box 513
5600 MB Eindhoven
The Netherlands

Eindhoven, August 1990
The Netherlands
A Bayes-Competing Risk Model for the Use of Expert Judgment in Reliability Estimation

F. P. A. Coolen¹, Technical University Eindhoven,
P. R. Mertens, Kemira bv,
M J Newby, Technical University Eindhoven²

Abstract

In an analysis of the reliability of heat exchangers a number of causes of failure and a number of potential failure patterns were identified. To allow a simplification of the analysis five independent groups of failure causes were defined and formed the basis of a competing risks model. Further, lack of data and poor quality data required the experience of "experts" to be used in a quantitative way through Bayesian methods. Lastly to simplify the elicitation of the prior densities a shape, scale and location parameter model for the failure time distributions was adopted.

INTRODUCTION

As part of a general review of reliability in a chemical process plant a study of the reliability of heat exchangers was undertaken¹. The heat exchangers fall into two groups, critical and non-critical. The critical exchangers operate at high temperatures and pressures and any fault requires an immediate shutdown of the plant, the non-critical exchangers operate under less extreme conditions and can tolerate some faults (a few leaking pipes, for example) without requiring a stop in production. Safety regulations also require regular testing of the plant, and a good record of uninterrupted and hazard free operation allows the required intervals between assessments to be extended, in other words a saving on shutdown and testing costs.

The study of the heat exchangers began with an examination of past failure and maintenance data. It became clear in this stage of the study that a number of factors made the recorded data useless without the mediation of a complex model, or without the incorporation of the experience and knowledge of the users. The problems with the data were manifold: recorded events are not always well defined; there are very few observations associated with any

¹ This work was carried out mainly by the first named author as part of an MSc project while a student at the Technical University Eindhoven.

² Address for correspondence: Faculty of Industrial Engineering, Technical University Eindhoven, Postbox 530, 5600 MB Eindhoven, Netherlands.

³ This article has been offered to Reliability Engineering and System Safety, and is not to be quoted without the authors' permission.
particular failure cause or mode; there has been a continuous change in the
design and the process conditions of the exchangers. However, there is among
the maintenance engineers, design engineers, and plant operators a significant
amount of knowledge and experience about the performance of the equipment
under different conditions, the effects of design changes, and the performance
of similar equipment in other plants.

The reliability problem is to specify a conditional reliability for each
heat exchanger given its past failure history, its maintenance history and any
changes in conditions or design. This function, \( R(t|t_0) \) defines the
reliability for a period \( t \) into the future given information today, \( t_0 \). There
are a number of ways of incorporating explanatory variables into a model to
reflect the effects of such things as temperature, pressure, choice of
material, maintenance policy etc. In reliability analysis the proportional
hazards model\(^2,3\) or the accelerated failure time model\(^2,4\) are often used to
show explicitly the influence of explanatory variables on the hazard rate or
reliability. However, the data available in the current study could not
support the estimation of parameters in these two particular models. A third
approach, commoner in epidemiology, is through the use of competing risks
models\(^5\), some proportional hazards models are also competing risks models, and
sometimes stratification is used in proportional hazards models to give a
model which lies between the two. Competing risks models are able to work
without requiring independence between the causes or types of failures, but
are then hard to interpret and difficult to estimate. Thus, in this study, a
competing risks framework with independent failure modes was chosen for the
underlying failure model.

In the second stage it was necessary to incorporate the information
available within the plant into the model. This was done by using a
straightforward Bayesian method after eliciting prior distributions of the
parameters of interest from the "experts". A second function of the Bayesian
approach is to lay the basis for the evaluation of the performance of the
experts as judges of failure behaviour and to quantify their performance.
Through establishing "scores" which measure the effectiveness of an expert a
feedback element can be incorporated to help the "experts" to improve their
own performance over time. In the long run the interaction between the
experts and the data is the most important feature of this approach. A good and systematic method of data collection and analysis opens the door to better decision making.

**COMPETING RISKS MODELS**

In a competing risks model with independent failures there are \( n \) failure types defined, and each failure type is described by the distribution, reliability function, density, or hazard rate denoted by \( F_i, R_i, f_i, \) and \( h_i \) where

\[
F_i(t) = P[T_i \leq t]
\]
\[
R_i(t) = 1 - F_i(t)
\]
\[
f_i(t) = \frac{dF_i}{dt}
\]
\[
h_i(t) = \frac{f_i(t)}{R_i(t)}
\]

for \( i = 1, \ldots, n \) and \( T_i \) is the time of failure due to the \( i \)-th cause. The model assumes that the times of failure, as random variables, are \( T_i \) and that the observed time of failure is then one of the \( T_i \). The time of failure is thus the minimum of the failure times \( T_f = \min(T_1, T_2, T_3, \ldots, T_n) \). Because the failures are assumed independent it follows that

\[
P[T_f > t] = P[T_i > t \ \forall \ i] = \prod_{i=1}^{n} R_i(t)
\]

so that

\[
R(t) = \prod_{i=1}^{n} R_i(t) \tag{1}
\]

and the hazard rate for the process is simply the sum of the individual hazard rates

\[
h(t) = \sum_{i=1}^{n} h_i(t). \tag{2}
\]

Conversely, the marginal distributions are the \( F_i \). Thus if a satisfactory grouping into independent failure modes is possible the competing risks model permits the analysis of each group separately as long as the parameters of the failure distributions of each group are functionally independent. Moreover, the Bayesian analysis for each group may also be done separately. After the failure distributions for each group have been established they may be combined according to (1) or (2) to give an overall reliability function or hazard rate. Since the definition of the groups is given by the "experts" and
because independence is assumed, expert judgment also enters into this part of
the model.

THE BAYESIAN BACKGROUND

In this section only a single failure time distribution is mentioned, however, in view of the competing risks assumptions this causes no problem for
each failure group may be treated separately and the results recombined at the
end. This approach also requires the experts to give independent assessments
of the priors for each failure group.

A standard Bayesian approach was used with the data entering through a
likelihood and the judgment entering through the prior density, the
combination of the two yielding the posterior density. In this article
attention is focussed on predictive distributions since they are functions of
the data alone and, moreover, allow probability statements to be about system
performance. For the user of this approach estimates of parameters themselves
are of less interest. The method was extended in a natural way to deal with
several priors obtained from a number of experts and to provide a weight or
score for each expert that reflected the quality of that expert in describing
failure behaviour. Thus an expert whose assessment was close to the observed
failure behaviour should receive a higher score than one whose assessment is
far from the actual events. In short, the closer the mode of the prior and
the likelihood the higher the score.

One Parameter Model

To simplify both the elicitation process and the calculation a discrete
prior was chosen for the parameter of interest. And again in the interests of
elicitation a shape, scale and location parameter family of distributions was
used for the failure model. Such a family is defined by a distribution,
G(t; \beta) with a single shape parameter, \beta, and mean \mu(\beta). A derived
distribution \(G_1\) is obtained by affine transformations of the time
variable, namely \(u = \left\{ \frac{1}{\beta} - \frac{\tau}{\beta} \right\}\), giving \(G_1(t) = G(u; \beta)\). More importantly in
this context \(\tau\) represents a "guarantee period" in which no failure can take
place, and the mean of the derived distribution, \(\mu'\), is given by

\[ \mu' = \vartheta \mu(\beta) + \tau, \]
so that
\[ \phi = (\mu' - \tau) / \mu(\beta). \]
Questions about the shape parameter and location parameter can be put as questions about mean, \( \mu' \); and the equation inverted to give a prior for \( \phi \).

In this particular problem the shape parameter \( \beta \) has been taken as a fixed value and interest centres on \( \phi \) and \( \tau \). The influence of the shape parameter will be discussed later. The prior density for \( \phi \) is used to define the guarantee period \( \tau \) as well as the posterior density. There are \( n \) experts each of whom specifies the prior for \( \phi \) by choosing a discrete distribution as follows. Each expert specifies in an interview a prior distribution for the mean value of the lifetime of the component. The expert is offered \( m \) intervals (not less than 3 and not more than 10) and asked to specify the probability that the mean of the life distribution lies in a particular interval. The intervals are \([0, a_1], (a_1, a_2], \ldots, (a_{m-1}, a_m]\) where, in principle, \( a_m \) is infinite but is here simply taken large enough to encompass all reasonable mean values. Thus expert \( j \) specifies a probability mass function \( p_{jk} \) where \( p_{jk} \) is the probability that the mean, \( \mu' \), of the distribution lies in an interval \((a_{k-1}, a_k]\). The location parameter is defined as

\[ \tau = \min_j \left\{ \max_k \{ a_k \mid p_{jk} = 0 \} \right\} \]

and the scale parameter lies in interval

\[ \left( \frac{a_{k-1} - \tau}{\mu(\beta)}, \frac{a_k - \tau}{\mu(\beta)} \right) \]

with probability \( p_{jk} \). In words, the location parameter is taken as the lowest plausible time in the opinion of the experts at which a failure can occur.

Let the prior for expert \( i \) be \( \pi_{ik} \), and the likelihood given a parameter value in the \( k \)-th interval be \( \ell_k = \text{likelihood}(\text{data} \mid \phi_k) \), set \( s_i = \sum_k \pi_{ik} \ell_k \), \( s_i \) is referred to as the score for expert \( i \), then the Bayes formula for the
posterior of expert $i$ is

$$P_{ik} = \frac{P_{ik} L_k}{s_i}.$$ 

This one parameter model is particularly easy to formalise as follows.

Intervals for prior $[0, a_1], (a_1, a_2], \ldots, (a_{m-1}, a_m].$

For calculating means $\bar{\alpha} = (\bar{\alpha}_1, \bar{\alpha}_2, \ldots, \bar{\alpha}_m)^T$, where $\bar{\alpha}_j = \xi_j a_{j-1} + (1-\xi_j) a_j$

for some $\xi_j \in [0,1]$ and $j=1\ldots m$

for Prior for expert $i$ $p_i = (p_{i1}, p_{i2}, \ldots, p_{im})$. 

Likelihood $\ell = (\ell_1, \ell_2, \ldots, \ell_m)^T$.

Overall prior $P = (p_{ij})_{nm}$.

Score vector $s = (s_1, s_2, \ldots, s_n)^T$.

Then $s = P \ell$.

Setting $S = \text{diag}(s_i)$,

$L = \text{diag}(\ell_j)$,

and $u_n = (1, 1, \ldots, 1)^T$, a vector of $n$ 1's

$u_m = (1, 1, \ldots, 1)^T$, a vector of $m$ 1's.

The vectors $u_n$ and $u_m$ are useful for computing sums, with these definitions we have $\ell = L u_m$, and $s = S u_n$.

The posterior densities can be summarised as an un-normalised version, $P_1$, and a normalised version, $P_0$, where

$$P_1 = PL$$

$$P_0 = S^{-1}P_1 = S^{-1}PL.$$ 

The estimates of the posterior mean are then simply $\bar{\alpha} = P_0 \bar{\alpha}$

We evaluate the underlying failure density, $f$, at an arbitrary value of $t$ and define
\[ f_k = f(t|\vartheta_k) \]
\[ f = (f_1, f_2, \ldots, f_m)^T \]

so that the predictive density for each expert evaluated at \( t \) is given in the vector

\[ \tilde{f} = P_0 f \]

In general if we define a list of \( q \) arbitrary times \((t_1, t_2, \ldots, t_q)\) at which the predictive density or reliability is required, and a row vector

\[ \vec{I}_k = \vec{P}_0 \]

In the same way if \( \mathcal{R} \) represents the reliability matrix with the same evaluation points as \( \vec{I} \),

\[ \mathcal{R} = (R_{ki}) = (R(t_i|\vartheta_k))_{mq} \]

then the predictive reliability is

\[ \tilde{\mathcal{R}} = P_0 \mathcal{R} \].

### A Single Weighted Posterior Density

The most natural way to construct a single posterior density from \( P_0 \) is to construct a weighted sum using a weight vector \( w = (w_1, w_2, \ldots, w_n) \) to yield a posterior

\[ \mathcal{P} = wP_0. \]

Because of the paucity of data, the lack of suitable comparisons, and the different backgrounds of the experts, the scores of the experts were used rather than calibration by the method of "seed variables". The weights \( w_i \) should reflect the performance of the experts and the easiest way to do this is to choose \( w_i \propto s_i \) and to calculate an appropriate norming constant so that the sum of the weights is 1, in our notation \( \sum w_i = 1 \). Now

\[ s^T P_0 = (S_n)^T P_0 = u_n^T s P_0 = u_n^T S SP_0 = u_n^T S(S^{-1} P L) = u_n^T P L = u_n^T P_1 \]

showing that this version of the posterior is simply the sum of the
un-normalised posteriors. To find the appropriate norming constant calculate the sum

\[ s^T \mathbf{P} \mathbf{u}_m = u_n^T (\mathbf{P} \mathbf{u}_m) = u_n^T \mathbf{s}. \]

Thus the norming factor is the sum of the scores \( |s| = \sum_{i=1}^{n} s_i \). To conclude the weighting vector is simply \( w = s^T / |s| \).

In summary:

- Weight vector \( w = s^T / |s| \)
- Posterior density \( \mathbf{P} = w \mathbf{P}_0 \)
- Posterior mean \( \tilde{\mathbf{t}} = w \mathbf{t} \)
- Predictive density \( \tilde{\mathbf{f}} = w \tilde{\mathbf{f}} \)
- Predictive reliability \( \tilde{\mathbf{R}} = w \tilde{\mathbf{R}} \)

Within the Bayesian scheme the elegance of the approach breaks down a little when we consider the hazard rate. It is easiest to show the problem in a general case. Consider a model \( f(t|\theta) \) with likelihood \( l(\text{data}|\theta) \) and prior \( g(\theta) \) for \( \theta \). The posterior for \( \theta \) given by,

\[ g(\theta|\text{data}) = \frac{l(\text{data}|\theta)g(\theta)}{\int l(\text{data}|\theta)g(\theta) d\theta} \]

distance density \n
\[ \tilde{f}(t|\text{data}) = \int f(t|\theta)g(\theta|\text{data}) d\theta \]

and predictive reliability

\[ \tilde{R}(t|\text{data}) = \int R(t|\theta)g(\theta|\text{data}) d\theta. \]

The reliability and the density stand in the correct relationship to each other, that is \( \tilde{I} = -\frac{d}{dt} \ln[\tilde{R}] \) because we can differentiate under the integral sign with respect to \( t \). The model hazard rate is \( h(t|\theta) = -\frac{d}{dt} \ln(R(t|\theta)) \), the hazard rate for the predictive distribution is \( \tilde{h}(t|\text{data}) = -\frac{d}{dt} \ln(\tilde{R}(t|\text{data})) \), and clearly

\[ \tilde{h}(t|\text{data}) \neq \int h(t|\theta)g(\theta|\text{data}) d\theta \]
because
\[
\frac{d}{dt} \ln \left\{ \int R(t | \theta) g(\theta | \text{data}) d\theta \right\} \neq \frac{d}{dt} \left\{ \int \ln[R(t | \theta)] g(\theta | \text{data}) d\theta \right\}.
\]

In short the operator \( \frac{d}{dt} \) which transforms a reliability function into a density is linear and commutes with integration in the present model and the operator \( \frac{d}{dt} \ln \) which transforms a reliability function into a hazard rate is non-linear and does not commute with integration.

Thus a choice must be made for the hazard rate. However, since that Bayesian formalism works completely naturally for the densities and the distributions the most logical thing to do is to define the hazard rate from the current version of the distribution. In our formulation the model has a hazard rate \( h(t|\theta) = \frac{f(t|\theta)}{R(t|\theta)} \). Each expert (labelled i) has a predictive hazard rate
\[
\tilde{h}_{ki} = \frac{\tilde{f}_{ki}}{\tilde{R}_{ki}}.
\]
and the overall predictive hazard rate is
\[
\tilde{h}_j = \frac{\tilde{f}_j}{\tilde{R}_j}.
\]
While this may be a shortcoming in terms of an elegant formalism it is clear that the only sensible thing to do is to work with the densities and reliability functions and then to calculate the appropriate hazard rates.

Lastly, it is useful in assessing the future to have an estimate of the remaining life of the component. In this case we need to calculate the life expectancy at time \( t \) (also called the residual mean life) defined as
\[
\mu(t) = E[T | T > t] = t - \frac{1}{R(t)} \int_t^\infty R(u) du.
\]
With the predictive reliability available we have an estimate of the life expectancy as
\[
\tilde{\mu}(t) = (R_j)^{-1} \sum_{t_i \geq t_j} R_i \Delta t_i \quad \text{for } t_j \leq t \leq t_{j+1}.
\]

**Updating the Model**

As new data become available the likelihood must be updated, and continuing with the notation above, write the likelihoods in a diagonal matrix then the
likelihood updated from time $\alpha$ to $\alpha+1$ is

$$L_{\alpha+1} = L'L_{\alpha}$$

the likelihood matrix for data accumulated up to time $\alpha$ multiplied by the likelihood matrix, $L'$, of the new observations. Thus while the data is accumulated the score vector is updated as

$$s_{\alpha+1} = P_{\alpha+1}u_m$$

and the weight vector as

$$w_{\alpha+1} = s_{\alpha+1}^T/s_{\alpha+1} , \text{ with } |s_{\alpha+1}| = u_m^T s_{\alpha+1}.$$  

The score vector provides feedback to the experts who must also periodically update their prior in the light of new data and in the light of known changes in design, maintenance, or operating conditions. In this case the prior is updated from $P$ to $P'$ and the rest of the changes follow through naturally in imitation of the arguments above. The hope is that over a long period of time the experts will improve their judgment of priors by using the weights as a measure of performance, and so in the ideal steady state situation the weights should be equal, that is $w_m = u_m/n$.

**Two Parameter Model**

In this situation much of the neat formalism of the one parameter model is lost. However, it is clear that the construction of the predictive density and the reliability function weighted by the scores of the experts should follow the route given above. Suppose the model density is $f(t|\beta,\vartheta)$ and that we again work with discrete priors. Write the prior for expert $e$ as

$$P_{ij}^e = \text{probability}[\beta \in I_i, \vartheta \in J_j]$$

where $I_i$ and $J_j$ denote the intervals for the parameters used in the elicitation process. Let $\ell_{ij}$ be the likelihood evaluated for the $i$-th and $j$-th intervals of $\beta$ and $\vartheta$, then the posterior for expert $e$ is

$$\pi_{ij}^e = \frac{\ell_{ij}P_{ij}^e}{s_e}$$

where $s_e = \sum_{i,j}^e \ell_{ij}P_{ij}^e$ is the score for expert $e$. In line with the one parameter model write:

- **Prior:** $P_e = (p_{ij}^e)$
- **Likelihood:** $L = (\ell_{ij})$
Scores: \( s = (s_e) \)

un-normalised posterior: \( P_{1}^{e} = P_{e} \odot L \), where \( \odot \) denotes a pointwise multiplication \( z_{ij} = x_{ij} \cdot y_{ij} \).

normalised posterior: \( P_{0}^{e} = \frac{P_{1}^{e}}{s_{e}} \)

In line with the above the appropriate posterior to use is the sum of the un-normalised posteriors scaled by the total score, \(|s| = \sum s_{e} \), that is

\[
\tilde{P} = \frac{1}{|s|} \sum_{e} P_{1}^{e}.
\]

The predictive density at time \( t \) is a double sum

\[
\tilde{\alpha}(t) = \sum_{i,j} \tilde{p}_{ij} \cdot f(t | \tilde{\beta}_i, \tilde{\gamma}_j),
\]

where \( P = (\tilde{P}_{ij}) \) and \( \tilde{\beta}_i \) and \( \tilde{\gamma}_j \) are representative values \( \tilde{\beta}_i \in I_i \) and \( \tilde{\gamma}_j \in J_j \). The other results follow easily by analogy with the one parameter model.

**CASE STUDY**

Here we report on the application of the above approaches to a reliability analysis of the critical heat exchangers. The study was carried out in three stages: the definition of risk groups; the elicitation of priors; and the consolidation into an overall reliability function.

**Risk Groups**

Five risk groups were defined. The division into risk groups is, of course, arbitrary but was based on extensive interviews with engineering, operational, and maintenance management at the plant. The aim was to produce a division into groups which can plausibly be regarded as statistically independent. The kind of criteria used to define the groups were:

a) is the cause internal to the plant or external to the plant;

b) is the cause controllable or not controllable;

c) the cause is a function of intensity of use;

and these gave rise to the five defined groups.

1 *Design and manufacturing faults.* For example problems concerned with materials, errors in manufacture etc. They are associated with early failure.

2 *Startup faults.* As the name implies these faults occur immediately
on or shortly after startup. Many human errors such as a spanner left in the exchanger after maintenance fall in this category.

3 Wear and tear other than in pipes. Failures of baffles and supports, etc.

4 Wear and tear in the pipes. Corrosion, leaking seals, erosion in bends. Careful consideration has to be given to the assignment of events as consequences of group 3 or group 4 causes.

5 Incidental faults. Consequences of events outside the subject of interest. For example blockage by contamination coming from another part of the plant.

Groups 1, 2 and 5 refer to a pipe bundle within a heat exchanger, or the heat exchanger as a whole; groups 3 and 4 refer to individual pipes.

Elicitation

The elicitation process has been outlined above with respect to the one parameter model. Failure groups 3 and 4 were assumed to be described by three parameter Weibull distributions with shape parameter 2. A prior for the mean life within failure groups 3 and 4 was obtained in interviews with the experts, and there was no confusion in the minds of the interviewees about what was requested (they knew the difference between mean, median and mode).

For failure groups 1 and 2 a failure chance was given because this is so near to being a discrete part of the overall life distribution; this approach implies a memoryless discrete distribution with the chance of failure depending on the number of startup attempts in a given period. The discrete memoryless distribution is the geometric distribution and it is used to calculate the chance of a successful startup given the number of attempts in a period. After the transient period where the chance of a failure during a startup plays a role, the reliability function for groups 1 and 2 is taken as constant, in other words for the rest of the time it is only necessary to consider groups 3 to 5. The effect of the discrete distributions would be seen as discontinuities in the overall reliability function.

For group 5 the failure time was assumed to be exponential because it seemed reasonable to regard it as a sum of external independent causes. In this case too an estimate of the mean time to failure was used, in keeping with the approach for groups 3 and 4.
The choice of a shape parameter $\beta=2$ for the Weibull distributions was largely determined by pragmatic reasons. It was clear from what data was available that some aging was taking place in groups 3 and 4; Pitner showed that a Weibull fitted well in an analysis of heat exchangers used in nuclear power stations; the value of 2 is conservative over the period up to the mean life. Lastly, since there was in some instances only one failure observed in these groups, we must take either an arbitrary value for some parameters, or use a prior distribution. The use of a prior for more than one parameter leads us into as yet unresolved difficulties of elicitation. One way to resolve the difficulties of elicitation is to attempt through a mind-experiment to obtain a description of a whole distribution function, but then the Bayesian approach must also change somewhat with the experts' distribution functions playing the rôle of the model distribution function.

**Example**

In this study there were eleven experts, called A to K. In a series of interviews the experts gave their estimates of the prior distribution of the mean life of a particular heat exchanger in the presence of only one of the defined causes of failure. In this early stage the priors for 11 critical heat exchangers were obtained, and there are plans to extend the study to less critical heat exchangers and other components. To illustrate the application of the approach an analysis for one of the critical heat exchangers is carried through. The example is very simplified, but serves to show the outputs analyses and outputs available from the model. The unit of time throughout is one month.

For failure groups 1 and 2 the mean of the experts opinion of the failure chance per startup was taken, and for both groups this chance was assessed as 0.058. This corresponds to using a deterministic prior as for group 5.

The model reliability function for groups 3 and 4 was assumed to be a Weibull,

$$R(t|\beta,\theta) = \exp\left\{ -\left[ \frac{t-\tau}{\theta} \right]^\beta \right\}$$

with density

$$f(t|\beta,\theta) = \frac{\beta}{\theta} \left[ \frac{t-\tau}{\theta} \right]^{\beta-1} \exp\left\{ -\left[ \frac{t-\tau}{\theta} \right]^\beta \right\}$$

and $\beta=2$.  

13
### TABLE 1: priors for group 3 causes

<table>
<thead>
<tr>
<th>expert</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.3</td>
<td>0.4</td>
<td>0.3</td>
</tr>
<tr>
<td>B</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.2</td>
<td>0.8</td>
</tr>
<tr>
<td>C</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>1.0</td>
</tr>
<tr>
<td>D</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.2</td>
<td>0.8</td>
</tr>
<tr>
<td>E</td>
<td>0.0</td>
<td>0.4</td>
<td>0.4</td>
<td>0.2</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>F</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>1.0</td>
</tr>
<tr>
<td>G</td>
<td>0.0</td>
<td>0.05</td>
<td>0.1</td>
<td>0.15</td>
<td>0.2</td>
<td>0.5</td>
</tr>
<tr>
<td>H</td>
<td>0.0</td>
<td>0.0</td>
<td>0.25</td>
<td>0.5</td>
<td>0.25</td>
<td>0.0</td>
</tr>
<tr>
<td>I</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.2</td>
<td>0.8</td>
</tr>
<tr>
<td>J</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.2</td>
<td>0.4</td>
<td>0.4</td>
</tr>
<tr>
<td>K</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.5</td>
<td>0.5</td>
</tr>
</tbody>
</table>

### TABLE 2: priors for group 4 causes

<table>
<thead>
<tr>
<th>expert</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.3</td>
<td>0.4</td>
<td>0.3</td>
</tr>
<tr>
<td>B</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.5</td>
<td>0.5</td>
<td>0.0</td>
</tr>
<tr>
<td>C</td>
<td>0.0</td>
<td>0.5</td>
<td>0.5</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>D</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.2</td>
<td>0.8</td>
</tr>
<tr>
<td>E</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.3</td>
<td>0.4</td>
<td>0.3</td>
</tr>
<tr>
<td>F</td>
<td>0.0</td>
<td>0.5</td>
<td>0.5</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>G</td>
<td>0.05</td>
<td>0.1</td>
<td>0.15</td>
<td>0.2</td>
<td>0.2</td>
<td>0.3</td>
</tr>
<tr>
<td>H</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>I</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.25</td>
<td>0.75</td>
</tr>
<tr>
<td>J</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.2</td>
<td>0.4</td>
<td>0.4</td>
</tr>
<tr>
<td>K</td>
<td>0.0</td>
<td>0.0</td>
<td>0.1</td>
<td>0.2</td>
<td>0.3</td>
<td>0.4</td>
</tr>
</tbody>
</table>

### TABLE 3: weights for experts

<table>
<thead>
<tr>
<th>expert</th>
<th>group 3 weights</th>
<th>group 4 weights</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.09</td>
<td>0.10</td>
</tr>
<tr>
<td>B</td>
<td>0.11</td>
<td>0.12</td>
</tr>
<tr>
<td>C</td>
<td>0.11</td>
<td>0.10</td>
</tr>
<tr>
<td>D</td>
<td>0.11</td>
<td>0.07</td>
</tr>
<tr>
<td>E</td>
<td>0.03</td>
<td>0.10</td>
</tr>
<tr>
<td>F</td>
<td>0.11</td>
<td>0.10</td>
</tr>
<tr>
<td>G</td>
<td>0.09</td>
<td>0.09</td>
</tr>
<tr>
<td>H</td>
<td>0.06</td>
<td>0.08</td>
</tr>
<tr>
<td>I</td>
<td>0.11</td>
<td>0.07</td>
</tr>
<tr>
<td>J</td>
<td>0.09</td>
<td>0.09</td>
</tr>
<tr>
<td>K</td>
<td>0.10</td>
<td>0.09</td>
</tr>
</tbody>
</table>
The priors for groups 3 and 4 are given in Tables 1 and 2. The intervals for the priors in both cases are defined by $a_1=24$, $a_2=48$, $a_3=72$, $a_4=96$, $a_5=120$, and $a_6=180$. The last value is rather arbitrary and is used because in practice the last interval cannot extend to infinity. Suppose that the available data consists of an observation period of 90 months which was terminated by a failure associated with group 4. Thus the likelihood for group 4 is the density function evaluated at the single time $t=90$, and for group 3 it is the reliability function evaluated at time $t=90$. The location parameter, $\tau$, for group 3 is easily seen from Table 1 to be 24, and in group 4 it is zero.

Lastly for group 5 the experts were asked to give a single estimate of the mean of an exponential distribution, that is a deterministic prior was used for the scale parameter of a Weibull distribution with shape parameter 1. This task was less demanding for the experts but preserved the general approach and allows the priors to be updated later. Although the model is exponential in form, the predictive density is a mixture of exponentials with a non constant hazard rate. The chosen mean times between failures were 60, 96, 120, 60, 240, 60, 600, 120, 240, 60, and 120 respectively. The lack of data meant that a likelihood function uniform over the parameter values was used.

In Figure 1 the predictive reliability functions, density functions and hazard rates are shown. In Table 3 can be seen the failure groups 3 and 4, the lack of data shows in the even weighting given to the experts, the weights are generally close to 1/11. However, the more pessimistic estimates given by E and H show up in their lower weights. In Figure 2 the overall predictive functions for groups 3–5 are shown. Figures 1 and 2 ignore the discrete part of the distribution, but this is easily applied as a correction to figures obtained from the graphs or by calculation. For example, the reliability after 72 months follows from the reliability of 30% evaluated for groups 3–5 and the reliability for the one initial startup and three (on average) other startups. Thus the reliability after 72 months is

$$R(72) = 0.30(1-p_1)(1-p_2)^3 = 0.30 \cdot 0.942^2 = 0.16,$$

a reliability of 16%. The hazard rate is affected additively by the terms $\ln(1-p_1)$ and $3\ln(1-p_2)$ and the mean residual life is unaffected as a predictor so long as the startups may be assumed to have happened in the past so that they cancel out in the conditioning required to assess the residual mean life.
FIGURE 1: Plots for groups 3-5

predictive reliability functions

predictive densities

predictive hazard rates

key

- group 5
- group 4
- group 3

FIGURE 2: Overall measures of reliability

overall predictive reliability

predictive density

predictive hazard rate

predictive residual mean life
It is also interesting to calculate the conditional reliability given that
the plant has been working without problem for a given time. In this example
the conditional reliability given that the plant has run for 36 months without
problem is required. Because we assume that initial startups have all
occurred in the past the reliability function for group 1 remains constant at
its value at time t=36 and thus cancels out of the problem during the
conditioning. To approximate the behaviour of group 2 with failure chance of
0.058 per attempt an exponential distribution is used, there are approximately
two startups per year and so the appropriate exponential has mean time between
failures 6/0.058. The conditional reliability function is shown in Figure 3
together with the unconditional reliability. The unconditional reliability
jumps immediately from 1 to 1−p₁ at time t=0 because the distribution for
group 1 is discrete⁹. The residual mean life is unaffected by conditioning,
and the hazard rate is reduced by the overall hazard rate at time t=36.

DISCUSSION

This paper has shown a simple and natural use of the Bayesian approach to
handle some problems in reliability and maintenance planning in a chemical
process plant. In particular, the use of the competing risks idea has allowed
the incorporation of some explanatory data in the construction of an overall
reliability function. The particular form of model chosen is also easy to
implement and does not require extensive numerical algorithms¹² to evaluate the
posterior, predictive and marginal densities required in many Bayesian
analyses. In practical terms the model described here is the kernel of a long
term data analysis project in which the correspondence between model
predictions and observed data will need to be analysed, and also one in which
the experts will be asked to update their priors in the light of data and the
weights assigned to their priors. Lastly, the presentation of information is
through an interactive system on a personal computer and so allows failure
patterns to be seen more easily through graphs like those used above than from tables of probabilities.

REFERENCES


<table>
<thead>
<tr>
<th>Number</th>
<th>Month</th>
<th>Author</th>
<th>Title</th>
</tr>
</thead>
<tbody>
<tr>
<td>M 90-01</td>
<td>January</td>
<td>I.J.B.F. Adan</td>
<td>Analysis of the asymmetric shortest queue problem</td>
</tr>
<tr>
<td></td>
<td></td>
<td>J. Wessels</td>
<td>Part I: Theoretical analysis</td>
</tr>
<tr>
<td></td>
<td></td>
<td>W.H.M. Zijm</td>
<td></td>
</tr>
<tr>
<td>M 90-02</td>
<td>January</td>
<td>D.A. Overdijk</td>
<td>Meetkundige aspecten van de productie van kroonwielen</td>
</tr>
<tr>
<td>M 90-03</td>
<td>February</td>
<td>I.J.B.F. Adan</td>
<td>Analysis of the asymmetric shortest queue problem</td>
</tr>
<tr>
<td></td>
<td></td>
<td>J. Wessels</td>
<td>Part II: Numerical analysis</td>
</tr>
<tr>
<td></td>
<td></td>
<td>W.H.M. Zijm</td>
<td></td>
</tr>
<tr>
<td>M 90-04</td>
<td>March</td>
<td>P. van der Laan</td>
<td>Statistical selection procedures for selecting the best variety</td>
</tr>
<tr>
<td></td>
<td></td>
<td>L.R. Verdooren</td>
<td></td>
</tr>
<tr>
<td>M 90-05</td>
<td>March</td>
<td>W.H.M. Zijm</td>
<td>Scheduling a flexible machining centre</td>
</tr>
<tr>
<td></td>
<td></td>
<td>E.H.L.B. Nelissen</td>
<td></td>
</tr>
<tr>
<td>M 90-06</td>
<td>March</td>
<td>G. Schuller</td>
<td>The design of mechanizations: reliability, efficiency and flexibility</td>
</tr>
<tr>
<td></td>
<td></td>
<td>W.H.M. Zijm</td>
<td></td>
</tr>
<tr>
<td>M 90-07</td>
<td>March</td>
<td>W.H.M. Zijm</td>
<td>Capacity analysis of automatic transport systems in an assembly factory</td>
</tr>
<tr>
<td>M 90-08</td>
<td>March</td>
<td>G.J. v. Houtum</td>
<td>Computational procedures for stochastic multi-echelon production systems</td>
</tr>
<tr>
<td></td>
<td></td>
<td>W.H.M. Zijm</td>
<td></td>
</tr>
<tr>
<td>Number</td>
<td>Month</td>
<td>Author</td>
<td>Title</td>
</tr>
<tr>
<td>---------</td>
<td>--------</td>
<td>---------------------</td>
<td>----------------------------------------------------------------------</td>
</tr>
<tr>
<td>M 90-09</td>
<td>March</td>
<td>P.J.M. van Laarhoven W.H.M. Zijm</td>
<td>Production preparation and numerical control in PCB assembly</td>
</tr>
<tr>
<td>M 90-10</td>
<td>March</td>
<td>F.A.W. Wester J. Wijngaard W.H.M. Zijm</td>
<td>A hierarchical planning system versus a schedule oriented planning system</td>
</tr>
<tr>
<td>M 90-11</td>
<td>April</td>
<td>A. Dekkers</td>
<td>Local Area Networks</td>
</tr>
<tr>
<td>M 90-12</td>
<td>April</td>
<td>P. v.d. Laan</td>
<td>On subset selection from Logistic populations</td>
</tr>
<tr>
<td>M 90-13</td>
<td>April</td>
<td>P. v.d. Laan</td>
<td>De Van Dantzig Prijs</td>
</tr>
<tr>
<td>M 90-14</td>
<td>June</td>
<td>P. v.d. Laan</td>
<td>Beslissen met statistische selectiemethoden</td>
</tr>
<tr>
<td>M 90-15</td>
<td>June</td>
<td>F.W. Steutel</td>
<td>Some recent characterizations of the exponential and geometric distributions</td>
</tr>
<tr>
<td>M 90-16</td>
<td>June</td>
<td>J. van Geldrop C. Withagen</td>
<td>Existence of general equilibria in infinite horizon economies with exhaustible resources. (the continuous time case)</td>
</tr>
<tr>
<td>M 90-17</td>
<td>June</td>
<td>P.C. Schuur</td>
<td>Simulated annealing as a tool to obtain new results in plane geometry</td>
</tr>
<tr>
<td>M 90-18</td>
<td>July</td>
<td>F.W. Steutel</td>
<td>Applications of probability in analysis</td>
</tr>
<tr>
<td>M 90-19</td>
<td>July</td>
<td>I.J.B.F. Adan J. Wessels W.H.M. Zijm</td>
<td>Analysis of the symmetric shortest queue problem</td>
</tr>
<tr>
<td>M 90-20</td>
<td>July</td>
<td>I.J.B.F. Adan J. Wessels W.H.M. Zijm</td>
<td>Analysis of the asymmetric shortest queue problem with threshold jockeying</td>
</tr>
<tr>
<td>M 90-21</td>
<td>July</td>
<td>K. van Harn F.W. Steutel</td>
<td>On a characterization of the exponential distribution</td>
</tr>
<tr>
<td>M 90-22</td>
<td>July</td>
<td>A. Dekkers J. van der Wal</td>
<td>Performance analysis of a volume shadowing model</td>
</tr>
<tr>
<td>Number</td>
<td>Month</td>
<td>Author</td>
<td>Title</td>
</tr>
<tr>
<td>--------</td>
<td>-------</td>
<td>---------------------</td>
<td>----------------------------------------------------------------------</td>
</tr>
<tr>
<td>M 90-23</td>
<td>July</td>
<td>A. Dekkers, J. van der Wal</td>
<td>Mean value analysis of priority stations without preemption</td>
</tr>
<tr>
<td>M 90-24</td>
<td>July</td>
<td>D.A. Overdijk</td>
<td>Benadering van de kroonwielflank met behulp van regeloppervlakken in kroonwieloverbrengingen met grote overbrengverhouding</td>
</tr>
<tr>
<td>M 90-25</td>
<td>July</td>
<td>J. van Oorschot, A. Dekkers</td>
<td>Cake, a concurrent Make CASE tool</td>
</tr>
<tr>
<td>M 90-26</td>
<td>July</td>
<td>J. van Oorschot, A. Dekkers</td>
<td>Measuring and Simulating an 802.3 CSMA/CD LAN</td>
</tr>
<tr>
<td>M 90-27</td>
<td>August</td>
<td>D.A. Overdijk</td>
<td>Skew-symmetric matrices and the Euler equations of rotational motion for rigid systems</td>
</tr>
<tr>
<td>M 90-28</td>
<td>August</td>
<td>A.W.J. Kolen, J.K. Lenstra</td>
<td>Combinatorics in Operations Research</td>
</tr>
<tr>
<td>M 90-29</td>
<td>August</td>
<td>R. Doornbos</td>
<td>Verdeling en onafhankelijkheid van kwadratensommen in de variantie-analyse</td>
</tr>
<tr>
<td>M 90-30</td>
<td>August</td>
<td>M.W.I. van Kraaij, W.Z. Venema, J. Wessels</td>
<td>Support for problem solving in manpower planning problems</td>
</tr>
<tr>
<td>M 90-31</td>
<td>August</td>
<td>I. Adan, A. Dekkers</td>
<td>Mean value approximation for closed queueing networks with multi server stations</td>
</tr>
<tr>
<td>M 90-32</td>
<td>August</td>
<td>F.P.A. Coolen, P.R. Mertens, M.J. Newby</td>
<td>A Bayes-Competing Risk Model for the Use of Expert Judgment in Reliability Estimation</td>
</tr>
</tbody>
</table>