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A Dynamic Risk Assessment Methodology for Maintenance Decision Support

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The failure mode and effect analysis (FMEA) is a widely applied technique for prioritizing equipment failures in the maintenance decision-making domain. Recent improvements on the FMEA have largely focussed on addressing the shortcomings of the conventional FMEA of which the risk priority number is incorporated as a measure for prioritizing failure modes. In this regard, considerable research effort has been directed towards addressing uncertainties associated with the risk priority number metrics, that is occurrence, severity and detection. Despite these improvements, assigning these metrics remains largely subjective and mostly relies on expert elicitations, more so in instances where empirical data are sparse. Moreover, the FMEA results remain static and are seldom updated with the availability of new failure information. In this paper, a dynamic risk assessment methodology is proposed and based on the hierarchical Bayes theory. In the methodology, posterior distribution functions are derived for risk metrics associated with equipment failure of which the posterior function combines both prior functions elicited from experts and observed evidences based on empirical data. Thereafter, the posterior functions are incorporated as input to a Monte Carlo simulation model from which the expected cost of failure is generated and failure modes prioritized on this basis. A decision scheme for selecting appropriate maintenance strategy is proposed, and its applicability is demonstrated in the case study of thermal power plant equipment failures. Copyright © 2016 John Wiley & Sons, Ltd.

Keywords: dynamic risk assessment; Bayesian updating; Monte Carlo simulation; failure mode; maintenance decision support

1. Introduction

Managing risks associated with equipment failure continues to elicit considerable research attention. In technical assets, risk is quantified by the product of probability of failure, and expected consequences should such a failure occur [1]. For this reason, firms implement maintenance strategies as a means of mitigating such risks. A maintenance strategy may be defined as 'the set of activities implemented with the objective of maximizing the availability and reliability of the equipment, in order to produce products of the desired quantity and quality' [2]. Well-known maintenance strategies mentioned in literature include the failure-based maintenance, time-based maintenance (TBM), design out maintenance (DOM) and condition-based maintenance (CBM).

Studies highlight the significant impact of maintenance risks and their associated costs on the total cost of asset ownership. For instance, Koronios *et al.*[3] mention that depending on the operating context, the asset's operation and maintenance phase can constitute as much as 70% of the total cost of ownership. Moreover, Mobley [4] notes that maintenance costs can constitute as much as 60% of manufacturing costs, thus underscoring the importance of well-executed maintenance programmes. For high-reliability installations, for instance offshore wind turbines or power generation plants, the costs apportioned to repairing failed components is often significant more so, in instances where such failure results in considerable power generation losses, penalty costs because of contractual power supply obligations or downtime delays attributable to spare part logistical lead-time delays[5].

Apart from failure-related costs, asset failure is associated with salient yet intangible risks. Examples of such risks include potential injury to persons in the vicinity of the failed equipment, for example broken-off shrapnel or projectile; industrial accidents[6]; potential environmental damage, for instance spillage of pollutants to the atmosphere[7]; or societal disruptions, for example power outages owing to equipment breakdown[8]. Thus, to mitigate such tangible (or quantifiable costs) and intangible negative impacts associated with the asset or equipment failure, maintenance practitioners are confronted with the challenge of selecting and implementing

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effective maintenance strategies. An important concern in this regard is the need of first and foremost assessing risks associated with equipment failure prior to formulating and deploying appropriate mitigation strategies[9].

Thus, in recent years, considerable research effort has been directed towards developing decision support frameworks for assessing asset failure risks and consequently formulating appropriate maintenance strategies which mitigate the impacts of equipment failure. Here, assessing the risks starts with identifying potential failure modes from which the failure modes are prioritized depending on their risk threshold[10]. The risk assessment process, in this regard, is premised on the fact that by focussing maintenance effort on failure modes with a high-risk threshold, a more effective allocation of resources may be achieved[9]. Moreover, targeting maintenance resources in this way enhances the availability and reliability of the equipment, through initiating better repair processes, better provisioning of spare parts, and could lead to a better understanding of focal root causes responsible for recurrent failure modes[9].

However, in the absence of a concise structure for assessing risks and consequently selecting appropriate mitigation strategies, practitioners often resort to ad hoc selection approaches where often expert intuition is largely relied on[11]. Such an ad hoc approach is, however, fraught with considerable risks of selecting inappropriate maintenance strategies thereby diverting the often scarce maintenance resources on non-critical failure modes. Moreover, such inappropriate strategies could imply sub-optimal root cause analysis consequently resulting in likely recurrence of similar equipment failure modes. Thus, in this regard, the need for quantifying risks and thus selecting appropriate maintenance strategies for operable assets is of utmost importance and, moreover, of strategic interest to the organization[10].

In maintenance decision-making, commonly discussed decision support framework for selecting appropriate maintenance strategies, whereof the concept of risk assessment is incorporated, includes the reliability centred maintenance[12] and the risk-based maintenance[13]. In particular, the reliability centred maintenance is widely applied in practice, whereof the risk assessment process is facilitated through the failure mode and effect analysis (FMEA)[14]. In the conventional FMEA, the failure mode criticality is assessed by computing the risk priority number (RPN), a risk measure that is a product of three risk metrics: occurrence (O), severity (S) and detectability (D), and depicted by Eqn (1) in the succeeding text:

$$RPN = O \times S \times D \tag{1}$$

In the RPN formulation, the occurrence metric evaluates the probability/likelihood of a failure mode occurring. The severity metric on the other hand measures the impact of the failure mode, while the detectability metric measures the likelihood of detecting the incipient failure mode prior to occurrence[12]. In the conventional form, the three RPN metrics are based on ordinal indices of which each metric is measured on a scale ranging from 1 to 10, the latter being the highest. Computing the RPN results in a priority index, which ranges from 1 to 1000, whereof the latter implies the highest criticality. Nonetheless, in the conventional form, the FMEA has been criticized for the following reasons[14–16]:

i Multiplying ordinal indices for the severity, occurrence and detection is questionable and argued as statistically invalid.
ii Estimating the severity, occurrence and detection metrics relies predominantly on expert assessment and largely delinked from empirical evidences that is usually derived from historical equipment failure data.
iii The FMEA is static in that the RPN is often not updated with the emergence of new sources of failure risks.
iv Owing to the static nature of the RPN, maintenance strategies are likewise seldom updated with the emergence of new sources of risks.

From the previously mentioned deficiencies, and in particular the concern, whereof the risk estimates are delinked from empirical evidences, the need for a more robust methodology for objectively assessing and quantifying risks is required, thus the motivation of this study. Importantly, this need is informed by among other factors, the recent advances and adoption of maintenance information management systems by both medium and large-sized organizations, whereof such systems have enhanced the collection of reliability and maintenance related data[17]. Thus, this also implies the need for a methodological approach for quantifying failure risks, in which these measured risks evolve dynamically as more data become available. On the other hand, such a dynamic approach should also leverage on expert knowledge, more so where sparse reliability or maintenance data are available. The latter would ideally be in the form of elicited expert estimates regarding risk metrics. Implemented correctly, the benefits of such a dynamic approach for assessing risks are significant: overall improvement in maintenance performance[18], operation and cost benefits[19], enhancement of asset/equipment knowledge[20], the latter linked to maintenance decision-making aspects such as root cause analysis or effective maintenance planning[21].

Thus, in view of the previously mentioned need and the expected benefits, a dynamic risk assessment methodology is proposed, and based on the Bayesian theorem. In the proposed methodology, risk metrics associated with equipment failure modes are assigned prior distribution functions, whereof the priors are elicited from experts. Next, the elicited priors are combined with observed evidences derived from empirical reliability or maintenance data, and here, the hierarchical Bayesian inference approach is adopted. The posterior distribution function derived as a result of the combined evidences is consequently incorporated as input to a Monte Carlo (MC) simulation model from which the expected cost of failure is generated and applied as a measure of the failure mode criticality. In this study, the expected cost failure is proposed as a measure of risk because the measure integrates risk metrics: (1) the probability of equipment failure and (2) the associated cost consequences. The consequences here correspond to cost components attributed to the specific failure mode, for instance power generation losses, spare part cost or repair cost.

By combining the elicited prior and the observed evidences into the hierarchical Bayes framework, the uncertainty associated with sparse data sets is taken into account. Moreover, in the framework, the derived posterior functions are evaluated for validity with respect to how closely each derived posterior function replicates the observed evidences incorporated into the hierarchical Bayes framework. The validity, in this regard, is evaluated through computing the deviance information criterion (DIC)[22], of which a low

DIC value correlates to a valid posterior function. For invalid posterior function, an alternative prior distribution function is assigned and its suitability with respect to deriving a valid posterior function evaluated in a similar way. In the final step of the proposed methodology, suitable maintenance strategies are selected for each failure mode based on its criticality as generated from the MC simulation model. For this purpose, a decision scheme[23] is proposed, and an important criterion for the decision scheme is the suitability of the selected strategy from a practical perspective.

This paper is organized as follows. In Section 2, recent improvements on the conventional form of the FMEA, which are relevant to this study, are discussed. In Section 3, the concepts underlying the hierarchical Bayesian methodology are described. In Section 4, the expected failure cost function used for failure mode prioritization is described, and in addition, a detailed description of the MC simulation modelling approach is presented. For the proposed failure cost function, the time to failure (TTF) function is used in lieu of the probability of occurrence, and on the other hand, distribution functions representing cost metrics such as spare part costs, or production losses are used in lieu of the severity risk metric. In Section 5, the application case is discussed where equipment failure modes in the thermal power plant of a selected use case are prioritized, and consequently, maintenance strategies selected. In Section 6, the managerial implications of the proposed framework, together with implications for practice and limitations, are discussed. In Section 7, important conclusion and direction for future work are drawn.

2. Improvements on the conventional FMEA

In recent years, several improvements to the conventional form of the FMEA are reported in the literature. Liu, Liu [15], for instance, review risk evaluation methodologies for the FMEA and discuss in detail improvements to the computation of risk in the FMEA. Examples of proposed improvements include incorporating enhancements such as multi-criteria decision-making methods (MCDM), linear programming and fuzzy rule-based approaches. Particularly, the previously mentioned authors mention the rather high proportion of fuzzy rule-based enhancements to the FMEA, a trend also corroborated in the FMEA literature[16,24,25]. Although the trend seemingly suggests the use of fuzzy risk metrics as an intuitive alternative to estimating crisp values for the FMEA risk metrics, the fuzzy rule-based methods are nonetheless subjective and largely rely on expert elicitations, without recourse to observed evidences, for example recorded failure events.

The earlier concerns are partly addressed by probabilistic modelling approaches, and in particular, models derived exclusively from empirical data sets[26,27]. In this context, statistical data fitting and parameter estimation approaches such as the maximum likelihood estimate are explored. Statistical data fitting methods are, however, premised on the availability of sufficient data sets, and often, will yield poor models and parametric estimates in instances whereof data sets are sparse. This is usually the case for rare failure events such as those characterizing high-reliability systems, for example power generation facilities or off-shore facilities[28,29]. For such sparse data sets, considerable uncertainties are introduced in the risk estimates in instances, where reliance is exclusively of statistical models and importantly where the risk estimates derived from such models are not updated with the availability of new information.

This gap motivates this study, and for this reason, the Bayesian inferencing approach is introduced, whereof the prior and observed evidences are combined through the posterior distribution functions. In this way, the uncertainties associated with sparse data sets are thus implicitly incorporated in the posterior function. Moreover, by combining the evidences in this way, the posterior functions representing the risk metrics are dynamically updated with the emergence of new information or failure data sets.

3. Bayesian approach to statistics

In the Bayesian inference approach to statistics, both the prior and observed evidences are combined and expressed through the joint posterior distribution. In this instance, the prior distribution function expresses the decision-makers' confidence regarding an unobserved event. As an example, the decision-maker may express subjectively the probability of occurrence of a failure event. On the other hand, the likelihood function in the Bayesian inference model is derived from observed evidences. As an example, the likelihood function may be derived from empirical data sets of the time between equipment failure events, whereof the function is derived from statistical data fitting. By combining the prior and observed evidences in this way, the parameter of interest, for example the probability of failure, may be inferred from the posterior function. The posterior function in this instance is derived from the Bayesian theorem and follows the formulation:

$$\pi(\eta/x) = \frac{L(x/\eta)\ \pi(\eta)}{\sum_{j=1}^{n} L(x/\eta)\pi(\eta)d\eta} \tag{2}$$

The term $\pi(\eta)$ represents the prior distribution, $L(x/\eta)$ the likelihood function, and $\pi(\eta/x)$ the posterior function.

In the form described in Eqn (2), however, the Bayes theorem presumes that both the prior and likelihood functions can be combined in a straightforward way. This is usually not the case, especially where the prior and likelihood functions belong to distinct family of distributions[30]. For instance, combining the exponential prior and the Weibull likelihood functions is rather straightforward as both functions belong to the exponential family of distributions. Thus, in this instance, the Weibull posterior function[31] is derived as a result. By contrast, combining, for instance the Lognormal prior and the Weibull likelihood functions, which belong to distinct families, is not straightforward, and in this instance, resolving analytically the posterior function would yield intractable mathematical formulations[31]. Additionally, estimating the parametric values for the prior functions is also not straightforward. For instance, consider an example whereof the TTF for a specified failure mode follows a two-parameter Weibull distribution with the parameters: shape (α) and scale (β). For this example, estimating the parametric values for the scale and shape parameter is also not straightforward, as multiple values are feasible.

The earlier concerns are addressed by the hierarchical Bayesian modelling approach, in which an approximation approach is implemented for resolving the intractable posterior distribution functions. Secondly, the approximation approach negates the need for estimating the parametric values for the prior distribution function, for instance the shape and scale parameters associated with the Weibull distribution. Rather, these values are sampled from a joint parameter space through a simulation approach.

To illustrate the hierarchical Bayes modelling concept, the convention by Kelly and Smith [30] is followed. Consider the following multi-stage prior distribution function given by Eqn (3), in which x denotes the parameter of interest, for instance the probability of failure:

$$f(x) = \int_{\Phi} f_1(x|\varpi) f_2(\varpi)\, d\varpi \tag{3}$$

In the previously mentioned equation, $f_1(x|\varpi)$ denotes the first stage prior which represents the variability associated with parameter x, conditioned on the vector ϖ. The vector ϖ here represents the parameters of the prior distribution, for example the Weibull's shape and scale parameters. In the hierarchical Bayes context, parameters of the prior distribution (e.g. the scale and shape parameter) are mathematically referred to as hyper-parameters. The term $f_2(\varpi)$ represents the second stage prior and denotes the uncertainty associated with the hyper-parameters, and here, uncertainty distributions are assigned to the hyper-parameters. Mathematically, such uncertainty distributions are referred to as hyper-priors.

To further illustrate the hierarchical Bayesian concept, consider the instance where the two-parameter Weibull prior distribution function is assigned to unobserved probability of failure (x) of the equipment. Mathematically, the two-parameter Weibull function is denoted by the equation:

$$f_1(x|\alpha,\beta) = \frac{\alpha}{\beta^{\alpha}} x^{\alpha-1} \exp^{-\left(\frac{x}{\beta}\right)^{\alpha}} \tag{4}$$

In the hierarchical Bayes form, the shape (α) and scale (β) hyper-parameters in Eqn (4) denote the first stage prior in the multi-stage prior described earlier on in Eqn (3) and further adapted in Eqn (5). In the second stage, and as seen in Eqn (5), the hyper-parameters are assigned uncertainty distributions with the hyper-prior parameters. For instance, the hyper-parameters may be assumed as Gamma distributed with the shape (ε) and scale (γ) parameters, with (ε,γ) denoting the hyper-priors. Assigning the hyper-priors in this instance negates the need for estimating the values of the Weibull hyper-parameters because the values here are sampled iteratively from joint parameter space generated by Gamma hyper-priors. The multi-stage prior for the two-parameter Weibull prior may be represented as follows[30]:

$$f(x|\alpha,\beta) = \iint f_1(x|\alpha,\beta,\varepsilon,\gamma)\ f_2(\alpha,\beta|\varepsilon,\gamma)\, d\alpha\, d\beta \tag{5}$$

The multi-stage prior depicted in Eqn (5) is resolved in the hierarchical Bayes approach by transforming the formulation into the directed acyclic graphical form[32], and in this way, the resulting posterior function is efficiently resolved through the Markov chain and MC simulation approximation approach. The interested reader is, however, referred to the work of Dezfuli, Kelly [31] and Kelly and Smith [30] for more detailed information, because the objective of this paper is not to describe in detail the hierarchical Bayes concept, but rather, apply the concept to the formulated research problem. The Bayes approximation approach is implemented using the openBUGS software, a freely available sampling technique based on the Gibbs sampler[32]. BUGS refer to the Bayesian inference using Gibbs Sampling.

4. The proposed methodology for dynamic risk assessment

In this study, the formulation for the cost-based FMEA[33] is adapted and applied for quantifying the equipment failure risk, whereof the expected failure cost is defined as

$$\text{Expected failure cost} = \sum_{i}^{n} F_i \times C_i \tag{6}$$

In the previously mentioned formulation, F_i denotes the characteristic failure mode, C_i the cost associated with failure mode i, and n the total number of failure modes observed over the specified period. From Eqn (6), the failure cost C_i may further be decomposed into several cost components:

$$\text{E (Failure cost)} = C_{spare\ \ part} + C_{production\ \ loss} + C_{repair} + C_{penalty} \tag{7}$$

In Eqn (7), the first term, that is the spare part cost, is incurred when the failure mode necessitates a component replacement. The second cost term, that is production loss cost, is associated with productivity losses during equipment downtime and attributed to the failure mode. For a power plant, the production loss is quantified in terms of electrical power generation losses. The third cost term, that is the repair cost, is calculated as a function of the diagnostic time, repair time and personnel costs, whereof the latter is computed as a function of the number of maintenance technician(s) required and the unit labor cost. The forth cost term, that is the penalty cost, is associated with non-fulfilment of contractual power supply obligations owing to power plant unavailability attributable to the characteristic failure mode.

The cost components defined in Eqn (7) often vary depending on the failure severity. For instance, the characteristic failure mode may be detected at incipient stages, thus necessitating minor repair actions. The same characteristic failure mode may be detected at a more advanced deterioration state, thus necessitating major repair actions, the latter associated with significant failure costs. To model these failure mode scenarios and cost consequence combinations, the MC simulation is explored. Particularly, in MC simulation, the uncertainties associated with these combinations are addressed from which the probability of occurrence of the characteristic failure mode is generated from the TTF distribution of the failure mode. Similarly, the cost consequence associated with the failure mode is also sampled iteratively from statistical cost distributions specific to the failure mode.

However, prior to incorporating the input distributions to the MC simulation model, the posterior functions are first derived using the hierarchical Bayesian approach. This is achieved by first assigning prior distribution functions to the risk metric represented in Eqns (6) and (7). The assigned prior functions are combined with the observed evidences based on the empirical data sets. Assigning the prior function is particularly important for sparse data sets, in which sufficient observed evidences are not available, for instance where data sets representing the TTF of a specific failure mode are insufficient. The posterior function generated as a result of the combined evidences is next checked for validity, whereof the DIC[22] is measured. For high DIC values, alternative prior functions are assigned from which the derived posterior functions are checked for validity by further computing the DIC. As mentioned previously, the DIC evaluates how closely the derived posterior function replicates the observed evidences or empirical data sets incorporated in the hierarchical model alongside the prior function. In this regard, a low DIC value is desirable.

Once valid posterior functions are derived, the functions and parameter values are applied as input to the MC simulation model from which the expected cost of failure cost for each failure mode is generated. The simulation approach is implemented in the ModelRisk®, a MC risk analysis software [34] and an add-in in MS Excel. For each failure mode, the expected cost of failure is determined at an appropriate confidence threshold and in this study, the 95% confidence level is considered. In addition to deriving the posterior functions, subjective distribution functions are also elicited from experts where the elicitation process is applied to risk metrics, whereof empirical data are unavailable. These include metrics such as the repair time and the number of technicians required for a repair task. In this context, subjective distributions were considered, which include the Triangular and project evaluation and review technique (PERT) distribution, of which the minimum, average and maximum estimates were elicited. This is followed by prioritizing the failure modes at the 95th percentile of the simulated expected cost of failure after which maintenance strategies were selected following a decision scheme[23]. Figure 1 depicts an overview of the proposed methodology.

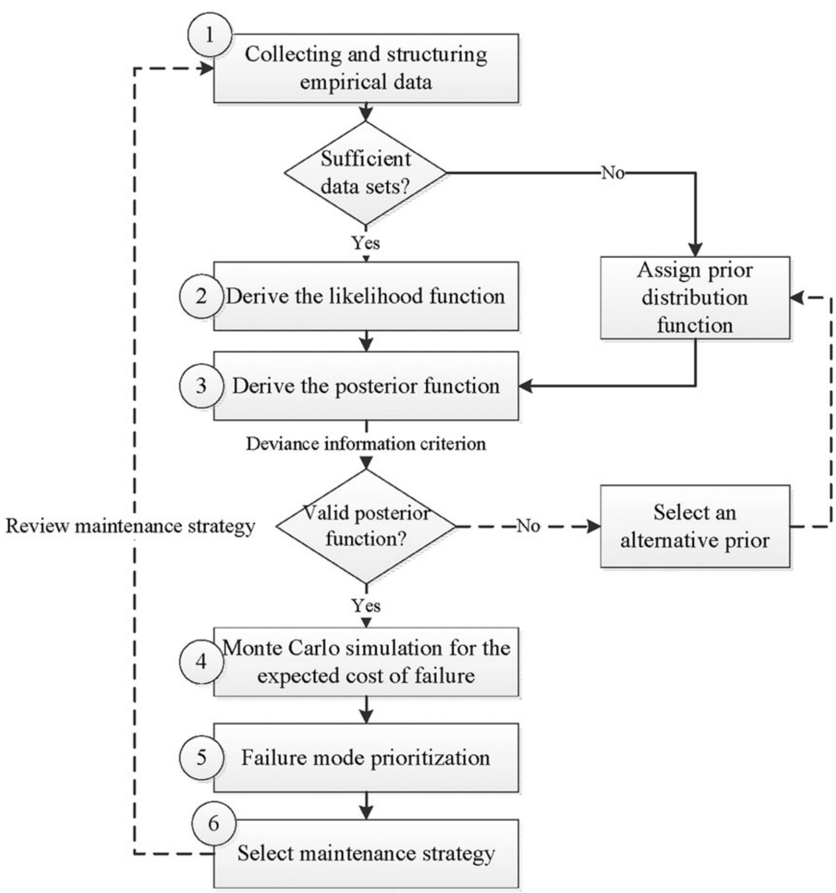

Figure 1. Proposed methodology for dynamic risk assessment

5. Application

5.1. Case study: thermal power plant

Thermal power plants provide crucial emergency power supply in the power generation industry. A primary advantage of such power plants is the comparatively shorter set-up time as compared with conventional power generation sources, for example nuclear or hydroelectric power generators. Typically, a thermal power plant comprises of inter-linked prime movers powered by different sources of energy, of which industrial diesel oil and natural gas are most commonly used.

The proposed methodology for dynamic risk assessment is applied in the case study of a thermal power plant, which consists of 10 diesel-powered engines coupled to electricity generators that supply power to the main electricity grid. Maintenance data sets were collected from the plant which represented 1003 failure modes recorded over a three-year period. Table I illustrates a sample of the maintenance data sets from which the risk metrics relevant to the study were extracted. These include the failure modes and cost metrics such as spare part cost or production loss during plant downtime, the latter costs derived from the repair information. Addition information such as the diagnostic time and repair time were further elicited from the experts and the estimates consequently assigned Triangular and PERT distributions.

5.2. Deriving the posterior distribution functions

The openBUGS script in the succeeding texts illustrates the hierarchical Bayes approach for deriving the posterior function for the TTF of the turbocharger vibration failure mode. In the script, the failure mode is assigned the two-parameter Weibull prior function. The hyper-parameters for the Weibull prior function: shape (α) and scale (β), are assumed Gamma distributed and assigned the hyper-priors (0.001, 0.001). In the script, the likelihood function is derived from the empirical data sets representing the TTF of the vibration failure mode. The vibration failure mode is represented by a series of the 21 data sets ($N = 21$), whereof the TTF is in hours, for instance, 278.9 h. The script is as follows:

```
model {
for (i in 1:N) {
        time to failure [i] ~ dweib (alpha, lambda)  # Weibull prior for the time to failure
        }
beta < -pow (lambda, -1/alpha)  # Weibull prior scale parameter
alpha ~ dgamma (0.001, 0.001) # assigned gamma prior
lambda ~ dgamma (0.001, 0.001) #assigned gamma prior
}
# data sets for the time to failure (in hrs.) of the turbocharger vibration failure;

list(N = 21, time to failure = c(278.9, 93.5,…, 1361)) # derives the likelihood function

# Values for initiating the script:
list (alpha = 1, lambda = 0.1)
list(alpha = 0.5, lambda = 0.1)
list (alpha = 2, lambda = 1)
```

In the script mentioned earlier, the Weibull's prior scale parameter (β) is re-parameterized using the following relationship[32]:

Table I. Sample of maintenance data specifying failure incidence and repair information

		Reported failure incidence		Engine re-start after repair			Repair information	
Serial no.	Failure mode	Date	Time	Date	Time	Time to next failure (h)	Value of spare parts used (EUR)	Production loss (MWh)
1	Cable insulation damage	14/01/11	6:51	14/01/11	07:15	361.9	53	23
2	Turbocharger vibration failure	24/01/11	6:30	24/01/11	10:21	278.9	98	87
3	Unsecured motor mounting	29/01/11	9:22	29/01/11	10:21	9807	30	154
4	Stuck roller guide because of loss of clearance	29/01/11	2:31	29/01/11	03:48	163	120	94

$$\lambda = \frac{1}{\beta^{\alpha}} \tag{8}$$

The parameter (λ) is also assumed as Gamma distributed with the hyper-priors (0.001, 0.001). To run the script, the Markov chains are initiated, whereof the values for alpha (α) and lambda (λ) are specified. Thereafter, the script is run first for 1000 iterations to allow for convergence of the Markov chains and followed by 199 000 iterations from which the parameter values for the posterior function are estimated[31]. Figure 2 illustrates the posterior Weibull distribution function parameters α and λ of the turbocharger vibration failure mode.

Table II summarizes the statistical values for the posterior parametric distributions derived from the hierarchical Bayes model of the turbocharger vibration failure mode. The statistical values further depict the lower bound, mean, upper bound and standard error values. The MC error is further depicted for each parametric estimate, whereof the MC error evaluates the quality of convergence of the Markov chains representing the parameter of interest, for instance the shape hyper-parameter of the TTF. Usually, a small MC error value is desirable and indicative of good convergence of the Markov chains[32]. From the results in Table II, the standard errors for the parametric estimates are relatively low, which from a statistical point of view indicate acceptable estimators for the posterior function parameters.

The derived posterior functions are also evaluated for validity with respect to replicating the empirical data incorporated in the script, whereof the validity check evaluates the appropriateness of the selected prior function. Table III depicts the DIC values for alternative prior functions assigned for modelling the turbocharger vibration's TTF. As depicted, the two-parameter Weibull prior is indicated as best replicating the observed TTFs because of the relatively lower DIC value as compared with the other alternative priors. Comparing also the *p*-values derived from statistical distribution fitting using the maximum likelihood estimate approach, the Weibull prior is likewise suggested as the most appropriate prior for modelling the observed TTFs.

However, one will also note that the Gamma distribution closely replicates the observed data sets as indicated by both the DIC value and also the *p*-value. As a result, the Gamma function could likewise be considered as an appropriate prior for modelling the TTF of the turbocharger vibration failure. By contrast, the Lognormal model least replicates the observed TTFs owing to the relatively higher DIC value and significantly lower *p*-value as compared with the two-parameter Weibull distribution. Following a similar approach, alternative prior models were also assigned to the severity or cost metrics earlier on denoted by Eqns (6) and (7). For the spare part cost, for instance, the Lognormal prior, it was determined as the best model based on its DIC value. The script in the succeeding texts illustrates the Lognormal spare part cost model for the turbocharger vibration failure mode. In the script, the Lognormal prior is associated with two parameters: log-mean (μ) and log-standard deviation (σ) of which the log-mean is modelled as uniformly distributed with a mean and standard deviation respectively of (0.001, 10). The log-standard deviation, on the other hand, is modelled as Gamma distributed with the hyper-prior parameters (0.001, 0.001). The script is as in the succeeding text:

```
model {
for (i in 1:N) {
        cost [i] ~ dlnorm (mu, tau)  # Lognormal prior for the spare part cost
        }
mu ~ dunif (0.001, 10.0)
tau < - 1/pow(sigma,2)
sigma ~ dgamma (0.001, 0.001)
}
# data sets for the spare part cost associated with the turbocharger vibration failure
list (N = 21, cost = c(98, 5, 17,…, 115)) # derives the likelihood function
# values for initiating the script:
list(mu = 1, sigma = 2)
```

The log-standard deviation parameter (σ) in the previously mentioned script is re-parameterized following the expression in the succeeding text[32]:

$$\tau = \frac{1}{\beta^{\alpha}} \tag{9}$$

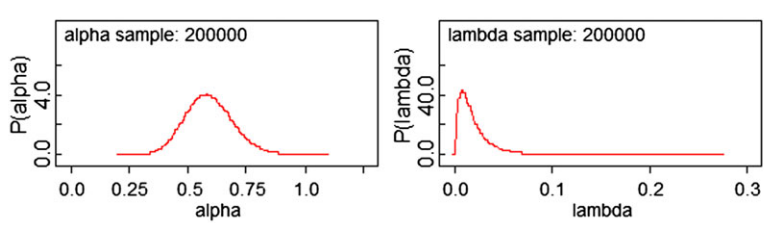

Figure 2. Distribution for the Weibull's posterior function parameters of the time to failure

Table II. Summary for the posterior distributions for the turbocharger vibration failure mode

Time to failure [hours]						
Weibull		*LB*	*Mean*	*UB*	*Standard error*	*MC error*
	Shape (α)	0.434	0.59	0.761	9.71×10^{-3}	1.14×10^{-3}
	Lambda (λ)	0.002685	0.01978	0.0634	1.64×10^{-3}	1.71×10^{-4}
Production downtime (h)						
Weibull		*LB*	*Mean*	*UB*	*Standard error*	*MC error*
	Shape (α)	0.584	0.734	0.888	5.43×10^{-2}	2.84×10^{-4}
	Scale (β)	4.369	6.583	9.277	1.38×10^{-1}	2.14×10^{-3}
Spare parts cost (EUR)						
Lognormal		*LB*	*Mean*	*UB*	*Standard error*	*MC error*
	Mu (μ)	5.712	7.43	8.854	1.25×10^{-1}	5.89×10^{-4}
	Sigma (σ)	1.134	2.953	3.958	8.81×10^{-2}	2.02×10^{-4}
Number of technicians						
PERT		*LB*	*Mode*	*UB*		
		1	2	4		

Table IV summarizes the posterior distribution functions and parametric estimates associated with the turbocharger vibration failure mode. The production downtime in this instance is used to compute the opportunity cost of lost electrical power generation (in MWh) attributable to the vibration failure mode. On the other hand, the estimates for the number of technicians required were elicited as 'best guesses' and consequently modelled using the PERT distribution whereof the minimum, average and maximum number of technicians were elicited[34]. The summarized posterior distributions and the parametric estimates derived for the failure modes formed the input into the MC simulation model from which the expected failure cost was simulated and used as the basis for the prioritization process.

5.3. *Failure mode prioritization*

In the failure prioritization step, whereof the posterior functions were applied as input to the simulation model, the expected failure cost was simulated by sampling in each simulation run, 10 000 independent MC samples. Thereafter, a total of 100 simulation replications were implemented from which the expected failure cost was generated as per Eqns (6) and (7). Figure 3 visualizes the histogram overlay plots for the 100 MC simulation replications for the expected failure cost of the turbocharger vibration failure mode. The *x*-axis of the plots depicts the simulated expected failure costs, while the *y*-axis depicts the probability values at each instance of the expected failure cost distribution. Moreover, the plot visualizes the expected cost values at the 5th and 95th percentiles, whereof as depicted, one would ideally expect that 90% of the failure cost values would fall with the range of between 91 040 and 92 040 euros. The plots also depict the average expected failure cost distribution (appearing in bold) within the overlay. The statistical measures for the evaluated failure modes are further summarized in Table IV.

As observed from both the expected failure cost overlay plots and the statistical measures for the turbocharger vibration failure mode, the mean percentage (standard error) in this instance is relatively low (<1%). Likewise, the mean percentage (standard errors) for the evaluated failure modes is likewise within acceptable ranges (~3%). On the basis of the simulated expected cost values, the failure modes were ranked, whereof the failure modes associated with the highest cost values were ranked as the most critical. The expected cost value at the 95th percentile was viewed as a plausible threshold for evaluating the criticality since statistically, 95% of the expected failure cost values will ideally fall within this percentile range [35,36].

As also observed from the expected cost value ranges, selecting the mean threshold values would likewise yield similar prioritization results. This is because the expected cost value ranges for the failure modes do not significantly overlap with each other. For instance, the expected failure cost ranges for the 'thrust bearing failure' (98,825; 103,132) and 'turbocharger vibration' (90,799; 92,379), although closely valued, do not seem to overlap. Thus, choosing the mean threshold value for these failure modes would likewise yield the same prioritization results, that is a lower criticality ranking for the 'thrust bearing failure'. In the event of overlaps between the expected cost distributions of closely valued failure modes, care should be exercised, and in this regards, more MC

Table III. DIC and *p*-value analysis of alternative models for the turbocharger's vibration time to failure

	Model	Maximum likelihood function (*p*-value)	DIC
1	Two-parameter Weibull	0.4607	790.7
2	Gamma	0.3737	792.4
3	Exponential	0.137	797.1
4	Lognormal	0.092	805.1

Table IV. Failure prioritization for the thermal power plant failure modes

		Expected cost of failure (Statistics)					
Rank	Failure mode	Min	Mean	Max	Stand error.	% error	Cumulative failure cost
1	Cracked exhaust valve	497 782	504 868	513 441	3092	<1%	57.8%
2	Turbocharger turbine blade erosion	149 481	150 927	152 054	492	<1%	17.3%
3	Thrust bearing failure	98 825	101 454	103 132	841	<1%	11.6%
4	Turbocharger vibration failure	90 799	91 533	92 379	316	<1%	10.5%
5	Injector roller seizure	9258	9491	9783	93	<1%	1.1%
6	Faulty orifice plate	7037	7224	7410	71	<1%	0.8%
7	Turbocharger lubrication pipe abrasion	3183	3232	3286	26	<1%	0.4%
8	Cable insulation damage	2051	2167	2319	53	2.44%	0.2%
9	Loose sensor connection	1621	1711	1802	34	1.98%	0.2%
10	Axial compressor gasket failure	1235	1258	1293	33	2.62%	0.1%

samples should be drawn iteratively from their respective posterior input distributions (i.e. >10 000 samples). On the other hand, more simulation runs (>100 runs) could also be likewise be implemented[37].

Thus, from the summary of the criticality ranking illustrated in Table IV, the 'cracked exhaust valve' is ranked as most critical and cumulatively, the failure mode accounts for approximately 58% of the total expected failure cost. Similarly, the turbocharger related failure modes constitutes a significant proportion of the total expected failure costs (~28%), because three of the 10 most critical failure modes are linked to the turbocharger. This implies the need for implementing more robust maintenance strategies, which are targeted at mitigating the cracked exhaust valve failure mode and the turbocharger related failure modes. By doing so, as much as 85% of the total expected failure cost would be mitigated for the case power plant.

Figure 4 illustrates the Pareto criticality ranking at the component level and derived through aggregating the cost values for failure modes associated with the specific component. As observed in Figure 4, the severities at the component level are consistent with those of the failure modes. For instance, the engine valve component failure is determined as most critical, followed by failures of the turbocharger component. From the Pareto analysis, these critical components accounts for 82.4% of the total expected cost of failure.

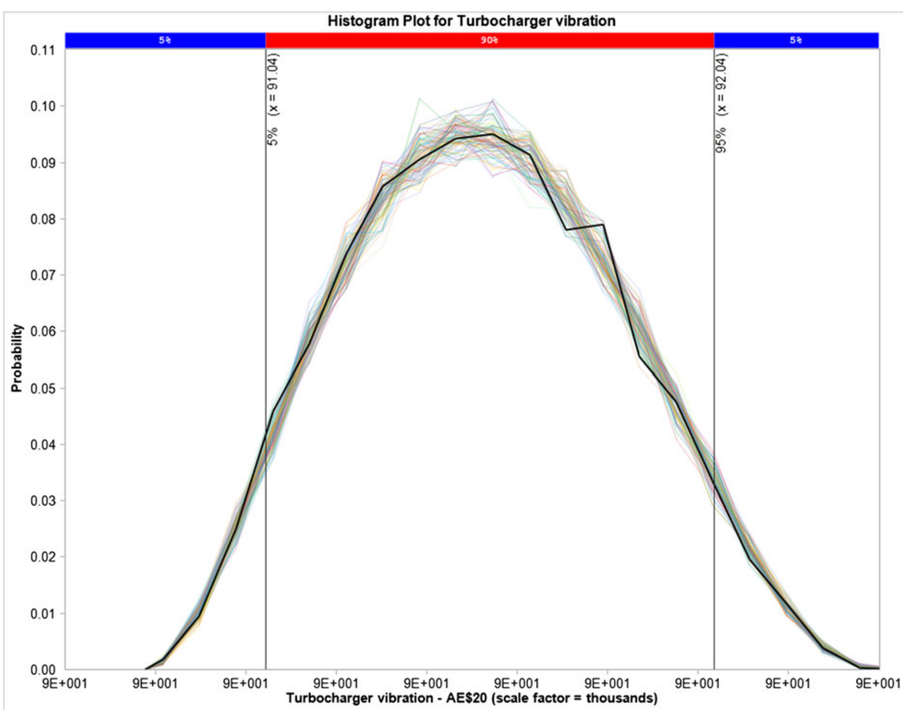

Figure 3. Monte Carlo simulation for the expected failure cost of the turbocharger vibration failure mode

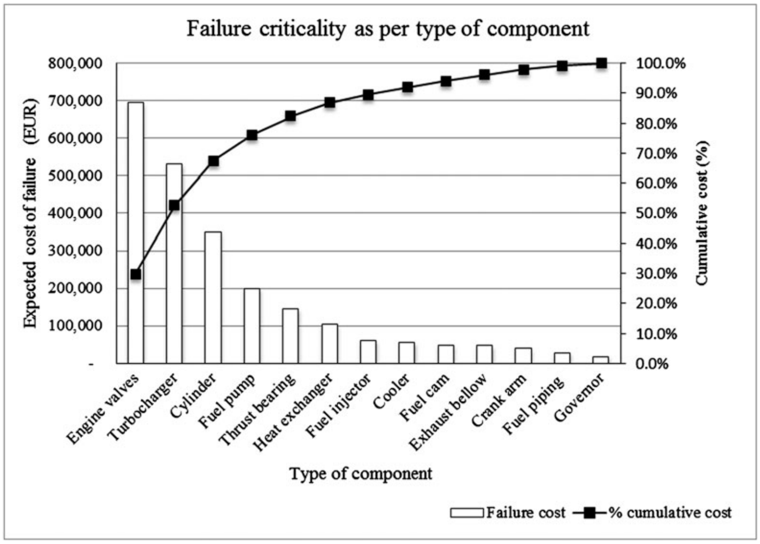

Figure 4. Pareto analysis depicting the criticality ranking at the component level

5.4. *Maintenance strategy selection process*

The decision scheme[23] illustrated in Figure 5 is adapted for selecting appropriate maintenance strategies of which five strategies are proposed. The first strategy, that is the failure-based maintenance, is adopted for components of low criticality, for instance fuel piping leakages and governor component failures (Figure 4). The second strategy, that is use-based maintenance or TBM, is, in this study, adopted for failures with evident component deterioration of which the deterioration pattern is derived from the historical reliability data[2] or expert knowledge of the component. For instance, the deterioration pattern may be observed through a reducing TTF with respect to operational time. The third strategy, that is CBM, is adopted for components of which the failure mode is

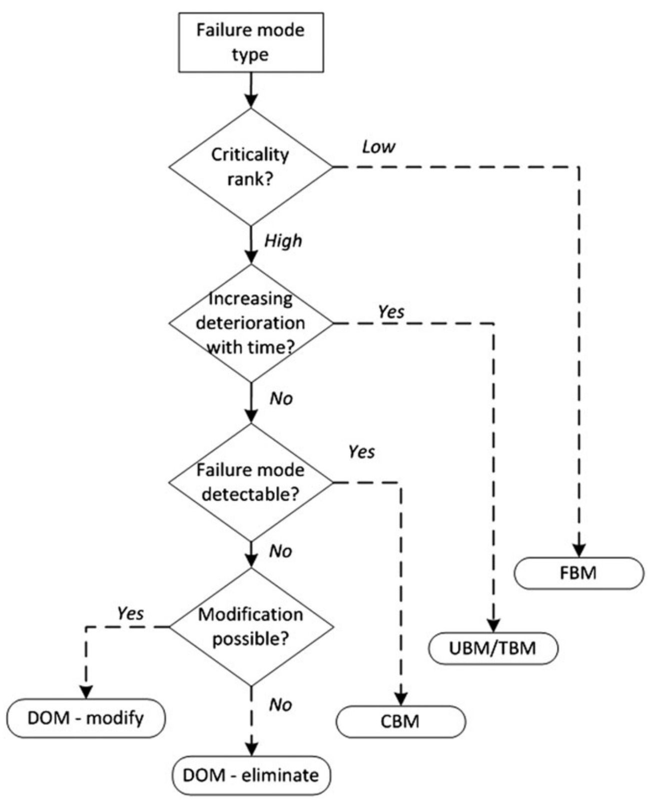

Figure 5. Maintenance strategy selection decision scheme

detectable. Examples here would include the turbocharger vibration failure because the component vibration is detectable through vibration analysis.

The forth strategy, the DOM may be adopted in two ways depending on the rigor of the modification process: (i) modifying the component or (ii) eliminating completely the failure mode. The modification strategy is adopted for components whereof design modifications are feasible from a technical perspective at the shop floor. Examples of on-site modifications would include installing additional clamping devices[38] for the lubrication piping with a view of mitigating the 'turbocharger lubrication piping abrasion' (Table IV). The re-routing in this instance would insulate the vibrating lubricant piping from contact with engine components, whereof the contact is a potential initiator of the abrasion failure mode.

The second DOM strategy is adapted for components of which implementing design modifications on-site is not feasible owing to factors such as the intricate component design. Examples of components affected in this regard include the exhaust engine valves[39]. For such intricate components, reference is often made to the original equipment manufacturer, where the specific design/manufacturing expertise can be sought. Although the decision scheme illustrated in Figure 5 assumes an independent allocation of the appropriate strategy, whereof each failure mode is assigned a distinct strategy, in practice, however, a combined allocation strategy may be adopted. For instance, the piping leakage failure mode may be eliminated through DOM strategy selected alongside a run-to-failure strategy given its low criticality. Design modification that may be implemented in this instance may also include re-routing or clamping the piping[38], thus avoiding initiation of the piping abrasion.

At a more detailed level, however, maintenance optimization may be attempted, more so for components of which the CBM and use-based maintenance /TBM strategies are implemented. In this instance, maintenance optimization models[40] may be used where optimized maintenance schedules, or intervention instances, are developed. The optimal intervention instances are largely applicable in the CBM strategy, whereof the interventions are linked to the component health as determined from prognostic information[41].

6. Discussion and limitations

6.1. Managerial decision support

In this article, a dynamic risk assessment methodology is proposed based on hierarchical Bayes approach. The methodology addresses two important flaw of the conventional FMEA: (i) the computation of RPN and (ii) the static nature of the risk metrics of which the metrics are seldom updated with the availability of new information. Both flaws are addressed through the hierarchical Bayes methodology, whereof prior distribution functions are assigned to risk metrics of interest, and in addition, the prior functions are combined with observed evidences. As a consequence, posterior distribution functions are derived. Assigning the prior functions negates the need for subjectively estimating the RPN metrics as is the case in the conventional FMEA methodology. Moreover, assigning the prior is important in instances where the observed evidences are sparse, and as a result, experts resort to the subjective estimates.

The second flaw is also addressed through the derived posterior distribution functions because in this instance, the posterior function evolves dynamically as more data becomes available, that is through a more robust likelihood distribution function. Moreover, the derived posterior functions are applied as input to a MC simulation model from which the expected cost of failure is generated thereby forming the basis for the failure mode prioritization process. The prioritized failure modes are also closely linked to maintenance strategy selection process, whereof a decision scheme is proposed. Additionally, the derived posterior function are evaluated for validity, thus ensuring that the selected prior yields a posterior function that closely mimics the observed evidences or data sets included in the hierarchical Bayes framework.

Additionally, incorporating the posterior functions as input into the MC simulation is viewed as an important step of further taking into account the uncertainties associated with the input posterior distribution functions. This is achieved through sampling independent values from the input distributions, and iteratively, aggregating these values as per the formulation of the expected failure costs earlier on defined in Eqns (6) and (7). The MC simulation is widely used for risk analysis, and particularly, propagating uncertainty[42] associated with the input risk metrics distribution functions. The MC simulation is also particularly attractive, as it is implemented as an add-in in MS Excel, whereof MS Excel is compatible with many organizational data bases.

The methodology also proposes a cost function—the expected cost of failure, as a measure of equipment failure risk. Using cost as a risk measure is particularly important for maintenance practitioners as cost is more understandable as compared with the RPN included in the conventional FMEA form. Moreover, the failure cost in this instance is linked to observed evidences as opposed to the RPN or the fuzzy-RPN metric that is widely applied currently[15]. The prioritization approach where the expected cost of failure is determined at specific percentile thresholds, for example 95th percentile, allows the decision-makers incorporate uncertainties associated with the expected failure cost.

In the final phase of the proposed methodology, a maintenance strategy selection scheme is proposed and consequently linked to the prioritized component failures. The decision scheme presents an intuitive and practical approach for assigning appropriate strategies to each component. As such, practical decision-making aspects such as the ability of detecting the failure mode or feasibility of designing out the component failure mode may be taken into account. Linking the maintenance strategy to the prioritized failure mode is particularly important, considering that the conventional FMEA is criticized for being static in the sense that the selected maintenance strategies are seldom updated with the emergence of new sources of risk[14]. Apart from facilitating the updating of the maintenance strategies, the proposed methodology also provides a viable basis for enhancing asset knowledge through capturing, storing, structuring, transmitting and retrieving data associated with important risk metrics, for instance the type of failure mode.

Overall, the benefits of the proposed methodology are underscored. Firstly, by quantifying risks using the expected failure cost not only avails maintenance practitioners with the opportunity of identifying risks more objectively but also assists the decision-makers allocate maintenance resources more effectively. Here, the decision scheme is rather beneficial from a practical perspective, and additionally, the scheme can be deployed alongside maintenance optimization models. This is because the proposed methodology also facilitates collection of maintenance data sets over time and as a result, maintenance optimization models can be applied. This is also because such optimization models require availability of sufficient data sets[40]. Recent advances in the development of maintenance optimization models has enhanced the uptake of such models among practitioners in industry[43].

Secondly, the failure mode prioritization approach also avails practitioners with the opportunity of performing a detailed root cause analysis thus identifying the potential initiators of recurrent failure modes. Such a prioritization process is viewed as ideal, particularly for medium-sized enterprises such as the thermal power plant evaluated in this study. This is because, compared with larger organizations or enterprises, medium-sized firms are often confronted with the need of optimizing operation and maintenance costs[17], and here, adopting a dynamic risk approach that focusses maintenance resources on priority failure modes is seen as beneficial. For instance, in this study, the turbocharger vibration failure mode was measured as critical; however, a reactive maintenance strategy was largely implemented at the case firm. Yet, from the risk assessment, the expected failure costs attributable to the turbocharger vibration failure mode are several orders of magnitude higher (Table IV) as compared with the actual costs of adopting a more pro-active approach, for instance off-line vibration analysis. Such a proactive approach could trigger repair actions prior to observed severe turbocharger vibration failure. In this way, the failure impact could be mitigated not only in terms of cost but also through avoidance of intangible consequences such as injury or fire hazards attributable to the turbocharger failure[44].

A similar conclusion could also be derived following the strategy selection framework suggested in Figure 5, whereof the decision scheme likewise suggests implementation of CBM strategy, for example through off-line vibration analysis. This is because the vibration failure mode is detectable by off-line/portable vibration monitors.

The proposed methodology is further useful to firms in different operation context, such as in the building services engineering. This is because, although the assessed failure risks may differ, nonetheless practitioners are confronted with the need of formulating more pro-active maintenance strategies for cost or safety-critical equipment, for instance heating systems[45].

6.2. Limitations

However, four main limitations should be mentioned. Firstly, the hierarchical Bayes model requires well-organized data sets that would allow the posterior functions to be determined proactively. This was, however, not the case for the case facility because data sets linked to the risk metrics were stored in separated data bases. For instance, the reliability data which specifies the risk metrics such as the TTF or the type of failure modes was for the case plant stored separately from that of the associated cost impact, for instance manpower or spare part cost. This aspect could be addressed through integrating the data bases storing data sets relevant for the risk metrics evaluated in the proposed methodology.

Secondly, the performance of the selected maintenance strategies would require measurement to ascertain the effectiveness of the deployed strategy. Two measurement approaches are thus suggested. The first approach entails actual implementation of the selected maintenance strategies, and here, the suggestion discussed in Waeyenbergh and Pintelon [23] could be adopted. The previously mentioned authors propose a seven-step strategy for implementing the maintenance strategy selected through a decision scheme such as discussed in this study. Consequently, the authors suggest quantitative performance measures for evaluating the maintenance effectiveness, for instance impact on the production output of the implemented strategy. Retroactively, a similar approach could be adopted, whereof the performance of the selected maintenance strategy could be evaluated through updated risk assessment, whereof the impact on the expected failure cost is measured. This is because the impact on the power generation losses is implicitly included in the failure cost. The second approach for measuring the maintenance strategy performance is through simulation modelling. Muchiri, Pintelon [46], for instance suggest a simulation approach for measuring the effectiveness of alternative maintenance strategies based on the impact on the overall equipment effectiveness. Retroactively, a similar approach is suggested, whereof the maintenance strategy performance is measured based on its impact on the expected failure cost, or the overall equipment effectiveness. Both the actual implementation and also simulation modelling approaches are, however, suggested for future work.

Thirdly, linking the hierarchical Bayes scripts to the standard MS excel worksheet from which the likelihood function could be derived from the empirical data sets is also required to ensure dynamic updating of the risk assessment. This aspect is also considered in the future work.

Lastly, it is important to concisely quantify intangible risks such as potential injury to personnel, or damage to the environment which could result from equipment failure. The proposed methodology is, however, limited in this regard. Hence, MCDM would be better suited. Thus, the proposed methodology could be extended to incorporate such MCDM modelling approaches.

7. Conclusion

In this paper, a dynamic risk assessment methodology for assessing risks associated with asset failure is suggested. The methodology addresses the flaw of the conventional FMEA form and is based on the hierarchical Bayes theorem and MC simulation. The methodology is demonstrated in the application case study of thermal power plant equipment failures, whereof prior distribution functions elicited from experts and empirical evidences associated with equipment failures are combined to generate posterior distribution functions. The posterior functions derived as a result are next incorporated as input into a MC simulation model from which the expected cost of failure is generated for the equipment failure modes. The expected cost of failure forms the basis of failure mode prioritization from which alternative maintenance strategies are assigned following a decision scheme with the objective of mitigating the prioritized equipment failures. The applicability of the proposed methodology is demonstrated in the application case of thermal power plant equipment failures, whereof its usefulness for decision support in maintenance decision-making is further demonstrated.

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