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A Hierarchical Bayesian Regression framework for enabling online reliability 1 estimation and Condition-Based Maintenance through Accelerated Testing 2 Leonardo Leoni^a, Filippo De Carlo^{a*}, Mohammad Mahdi Abaei^b, Ahmad BahooToroody^c 3 4 5 a. Department of Industrial Engineering (DIEF), University of Florence, 50125, Florence, Italy 6 Department of Maritime and Transport Technology, Delft University of Technology, Delft, The b. 7 Netherlands Marine and Arctic Technology Group, Department of Mechanical Engineering, Aalto University, 8 c. Finland 9

10 Abstract

11 Thanks to the advances in the Internet of Things (IoT), Condition-based Maintenance (CBM) has progressively become one of the most renowned strategies to mitigate the risk arising from failures. 12 Within any CBM framework, non-linear correlation among data and variability of condition 13 monitoring data sources are among the main reasons that lead to a complex estimation of Reliability 14 15 Indicators (RIs). Indeed, most classic approaches fail to fully consider these aspects. This work presents a novel methodology that employs Accelerated Life Testing (ALT) as multiple sources of 16 data to define the impact of relevant PVs on RIs, and subsequently, plan maintenance actions through 17 an online reliability estimation. For this purpose, a Generalized Linear Model (GLM) is exploited to 18 19 model the relationship between PVs and an RI, while a Hierarchical Bayesian Regression (HBR) is implemented to estimate the parameters of the GLM. The HBR can deal with the aforementioned 20 uncertainties, allowing to get a better explanation of the correlation of PVs. We considered a 21 numerical example that exploits five distinct operating conditions for ALT as a case study. The 22 23 developed methodology provides asset managers a solid tool to estimate online reliability and plan maintenance actions as soon as a given condition is reached. 24

Keywords: Condition monitoring, Condition-based maintenance, Hierarchical Bayesian Regression,
 Generalized Linear Model, Online Reliability Estimation

27 **1. Introduction**

In recent years, the advances related to the Internet of Things (IoT) technology have facilitated the implementation of an effective Condition-Based Maintenance (CBM) policy (Morimoto et al., 2017) (previously known as predictive maintenance policy (Prajapati et al., 2012)). The development of newer sensors and advanced data mining and feature extraction techniques have led to a more accurate

condition monitoring process. The major advantage of CBM compared to other Preventive 32 Maintenance (PM) policies is the ability to schedule maintenance actions depending on the monitored 33 condition of an asset, rather than planning maintenance interventions based on reliability parameters 34 such as the Mean Time To Failure (MTTF). Although CBM requires more efforts related to the 35 installment of sensors and much more responsiveness compared to Time-Based or Aged-Based PM 36 regarding logistics aspects and maintenance squad deployment, it could lead to a lower waste of 37 equipment useful life. According to the aforementioned statements, CBM has attracted the attention 38 of many researchers over the past decade (Cipollini et al., 2018; Hao et al., 2020; Hu et al., 2021; 39 40 Jiang et al., 2021; Omshi & Grall, 2021; Xu et al., 2021).

41 We could divide any CBM policy into three consecutive steps, which are denoted as i) data 42 acquisition, ii) data processing, and iii) maintenance decision-making (Jardine et al., 2006). The first step consists of collecting useful data, usually from sensors, while during the second one, noise 43 44 components are filtered out from the physical observations, and subsequently, data analysis is conducted. The combination of data acquisition and data processing is regarded as condition 45 46 monitoring, representing a precursor of any CBM. Finally, it is worth mentioning that distinct kinds of condition monitoring could be implemented, such as online condition monitoring (Wang et al., 47 2020), quasi-online condition monitoring (Zhang et al., 2021), and remote condition monitoring 48 (Memala et al., 2021). 49

Within the process of condition monitoring, there is a distinction between classification and 50 51 regression approaches. A classification approach aims at identifying the state of an asset-based on the monitored parameters. On the other hand, a regression framework aims to evaluate how a given 52 response variable denoting the degradation of the system develops in time based on some monitored 53 parameters. Moreover, in classification problems, the response variable is categorical, while in 54 regression methods, the response variable is real-valued (Murphy, 2012). Since condition monitoring 55 plays a pivotal role in conducting an efficient and effective CBM plan, there is an ongoing effort for 56 both classifications (Brito et al., 2022; Potočnik & Govekar, 2017; van den Hoogen et al., 2021) and 57 regression purposes (Dave et al., 2021; Ferrando Chacón et al., 2021). This fundamental vision has 58 59 resulted in the adoption of a wide variety of tools such as autoregressive moving average (ARMA) (Baptista et al., 2018), Fast Fourier Transform (FFT) (Gowid et al., 2015), FFT combined with SVM 60 (Pandarakone et al., 2017) and wavelet approach (Benkedjouh et al., 2018). The aforementioned tools 61 62 can analyze an input signal, eventually, remove noisy components, and study the degradation of 63 devices. A relevant example is a work proposed by Gowid et al. (2015), who applied FFT to analyze acoustic data and perform fault diagnosis in a centrifugal device. FFT is also used for fault detection 64 of bearings by Pandarakone et al. (2017), who subsequently adopted SVM for fault diagnosis. All the 65

aforementioned methods present some limitations. For instance, ARMA is characterized by a tuning
process to determine the most accurate parameters of the model, while FFT could lead to a loss of
features that vary over time because of its integral nature.

Meanwhile, Bayesian inference, such as Bayesian Network (BN) and Hierarchical Bayesian 69 70 Modelling (HBM), has also become a popular tool for condition monitoring purposes, thanks to its features, among which the ability to deal with source-to-source variability (Kumari et al., 2020). 71 72 Moreover, Bayesian Inference can provide better results than other parametric regression methods, such as Maximum Likelihood Estimation (MLE) (BahooToroody et al., 2020a). Finally, the adoption 73 74 of a hierarchy structure allows addressing the correlations among nonlinear data and the variation of non-stationary data, leading to a more coherent regression model compared to other classic 75 76 approaches (BahooToroody et al., 2019b). A relevant example of a BN-based condition monitoring 77 approach is presented by BahooToroody et al. (2019b). In their paper, they integrate an Empirical 78 Mode Decomposition with a Statistical Significant Test for noise removal, while they employ a Bayesian Network with a hierarchical structure to predict the time of the following pressure 79 80 exceedance. Another recent work by BahooToroody et al. (2020b) presented an HBR model to determine the probability of failure of a natural gas regulating and metering station based on the 81 monitored pressure. In their work, they modeled a discrete response variable through a normal logit 82 GLM, considering the pressure as the independent variable. Bayesian Inference has been proven itself 83 84 as a solid tool for reasoning under uncertainty, however, it presents some drawbacks. Specifically, Bayesian Inference is characterized by a greater mathematical complexity compared to other classical 85 approaches. The mathematical complexity requires a higher degree of knowledge and it could lead to 86 greater calculation time. However, the advances of specific tools have reduced the calculation time 87 and have taken easier the implementation of the Bayesian analysis. Moreover, the choice of the prior 88 89 distribution could be tough and an improper choice could lead to some undesired results. To avoid issues related to the calculation time, a non-informative prior could be used. 90

91 1.1 Background on Accelerated Life Testing

Within the context of reliability estimation, one of the main issues is related to data scarcity. Indeed, most probabilistic and reliability analysis suffers from a lack of data (Z. S. Ye & Xie, 2015), leading to high uncertainty in the estimation procedures (El-Gheriani et al., 2017). To overcome such limitations and satisfy reliability requirements, Accelerated Life Testing (ALT) has become a common practice over the past few years (Escobar & Meeker, 2006). In ALT, a given component is tested under operating conditions that are more severe than the standard operating condition (e.g., higher pressure than the nominal working pressure) (Elsayed, 2012), leading to a premature failure. 99 Accordingly, ALT allows to observe and to collect failure data in a shorter amount of time compared 100 to real-world application, resulting in safer operations. Moreover, making ALT before producing or 101 selling a piece of equipment gives more flexibility and precision during the definition of maintenance 102 or insurance policies.

103 ALT is treated through one of the following models (Moustafa et al., 2021): I) statistical models II) frailty models and III) distribution-free models. The first category of models assumes that the failure 104 times follow a given distribution with one or more parameters that depend upon the operating 105 condition. The statistical models are fully parametric and they allow to fit to the data different kinds 106 of distributions such as Weibull (Lin et al., 2017) or exponential (Haghighi, 2014). On the other side, 107 the second group of models exploits a random factor called fraility, which influences the hazard 108 109 function of the latent lifetimes (Liu, 2012). Examples of frailty model adoption can be found in Z.-S. Ye et al. (2013) and Roy (2018). Finally, the distribution-free models fall within the nonparametric 110 approaches and they have the advantage to avoid the requirement of finding a distribution that can 111 properly fit the available data. Even though non-parametric models could lead to conservative results 112 113 and do not require any distribution specification, parametric approaches such as statistical models could generate more accurate results given a proper choice of the distribution (Thomas, 2015). 114 Furthermore, they conceal more physical meaning, leading to a more informative description of the 115 problem. 116

Within the context of ALT, degradation data could be exploited instead of lifetime data during ALT. In this case, the evolution of one or more degradation parameters is studied and a degradation model is fit over the data. Degradation data contain more information compared to lifetime data, however, great knowledge of the equipment is required to choose a proper degradation parameter. Furthermore, linking the degradation to a RI should be based on sound reliability requirements (Thomas, 2015). It follows that building a degradation model could not always be a viable option. Considering the aforementioned statements, a lifetime parametric model is chosen for this study.

To conclude this section, it is worthwhile mentioning that Bayesian Inference has progressively 124 become more popular to deal with ALT. A recent work by Moustafa et al. (2021) integrates frailty 125 models and Bayesian inference to estimate the reliability of a multicomponent system through ALT 126 127 conducted both at the component and system level. Particularly, in their work, the authors employed the shared frailty model to address the relationships among the failures of distinct components, while 128 129 the Bayesian framework is adopted to incorporate the information coming from the component and the system level. Another recent work by Pang et al. (2021) exploited an HBM and ALT to predict 130 the RUL of a jewel-bearing accelerometer. First, ALT is conducted to determine the distribution type 131

and estimate the hyper-parameters of an HBM, which is later exploited to update the posterior distribution based on condition monitoring data. In the present work, ALT is exploited to extrapolate a relation between PVs and RIs through HBR, rather than finding an informative prior for Bayesian inference.

136 *1.2 Research gap and aim*

Despite all ongoing efforts, little attention has been devoted to determining how fluctuations in PVs 137 influence RIs (BahooToroody et al., 2019a), which is essential to grasp the changes in risk over time. 138 139 Moreover, most of the approaches related to condition monitoring of RIs fail to consider nonlinear correlation and multiple sources of data. As a result, developing a robust parametric tool capable of 140 estimating an asset's reliability performance over time, based on monitored operational parameters 141 and subsequently plan maintenance actions, is welcome. To this end, a methodology able to schedule 142 maintenance according to the variation of PVs is presented in this paper. For this purpose, after 143 extracting failure data from ALT, an HBR is employed to estimate the characteristic parameters of a 144 GLM linking the PVs and one RI. Lifetime data are considered instead of degradation data due to the 145 less knowledge requirement and the easiness to link a RI. In this context, the most common approach, 146 147 which is the MLE (Pascual et al., 2006), neglects the variability among distinct sources of data. Conversely, a Bayesian network with a hierarchical structure allows us to consider source-to-source 148 149 variability, leading to an accurate explanation of the correlation of PVs even when multiple data sources are present. Moreover, Bayesian approaches allow users to insert available knowledge, which 150 151 could be considered as supplementary data. This feature could also be useful to drive the analysis in case of data scarcity when expert judgments or prior knowledge are available. For instance, within 152 the context of ALT, the distribution coming from similar equipment could be used as a prior choice, 153 reducing the number of tests to perform. However, the amount of information inserted within the 154 prior distribution should be dosed carefully to avoid a completely prior driven calculation. On the 155 other hand, the adoption of GLM allows overcoming the main limitation of the parametric statistical-156 based models, which is fitting a specific distribution to the data. Indeed, GLMs are more flexible 157 compared to other approaches since they can consider a wide range of probability distributions for 158 the data, bypassing the assumption of normal error relationships between independent and dependent 159 variables (Guisan et al., 2002). Furthermore, they have demonstrated high efficiency and the ability 160 to deal with nonnormal response variables (Yeganeh & Shadman, 2021). 161

It is worthwhile mentioning that, in the context of reliability analysis, condition monitoring, and ALT,
Bayesian techniques have become popular tools. However, few works related to HBM, and more
specifically HBR, employed to process data coming from ALT are present. Besides, there is still

space to consider a continuous response variable within an HBR framework as recommended by 165 BahooToroody et al. (2020b). Finally, most of the statistical-based works related to ALT are mainly 166 focused on determining the reliability parameters, while the subsequent exploitation of the statistical 167 model from a condition monitoring perspective is disregarded. In contrast, this task is often carried 168 out in case a degradation model has been implemented. Accordingly, during the last phase of the 169 developed methodology, a proposal of maintenance tasks planning based on the monitored PVs and 170 the subsequent online reliability estimation is presented. The developed framework is implemented 171 172 on data extracted from ALT conducted with five distinct operating conditions.

The remainder of this paper is organized as follows; Section 2 describes the material and methods, while Section 3 is about the developed methodology. Section 4 illustrates the implementation of the methodologies in the numerical example adopted as a case study, while Section 5 discusses the results. Finally, conclusions and future developments are presented in Section 6.

177 2. Material and Methods

178 2.1 Hierarchical Bayesian Modelling

The main aim of any statistical inference is to deduce the properties or features of a population after analysing a sample of data extracted from the population itself. The HBM is a renowned statistical tool that allows conducting inference based on real-world observations through the Bayes Theorem (Eq. 1) (El-Gheriani et al., 2017).

183
$$\pi_1(\theta|x) = \frac{f(x|\theta)\pi_0(\theta)}{\int_{\theta} f(x|\theta)\pi_0(\theta)d\theta}$$
(1)

where θ is often a vector that denotes the unknown parameters to infer. $\pi_1(\theta|x)$ identifies the 184 185 posterior distribution, representing the updated knowledge on the parameters of interest after observing the available data and conducting the inference. The posterior distribution is given by the 186 product of the likelihood function and the prior distribution, which are respectively referred to as 187 $f(x|\theta)$ and $\pi_0(\theta)$. Accordingly, the Bayesian inference assigns a prior probability distribution to θ , 188 rather than considering it as a fixed value such as the frequentist approaches (Garthwaite et al., 2002). 189 Particularly, the HBM is named after exploiting a multistage or hierarchical prior, expressed by Eq. 190 2 (Kelly & Smith, 2011). 191

192
$$\pi_0(\theta) = \int_{\phi} \pi_1(\theta|\varphi) \pi_2(\varphi) d\varphi$$
(2)

193 where $\pi_1(\theta|\varphi)$ is called first-stage prior distribution, representing the variability of θ , while φ is a 194 vector in case the distribution of θ is a multi-parameters distribution. For instance, let θ be 195 characterized by a normal distribution, φ would be a two-element vector representing the mean and 196 the standard deviation of the normal distribution. However, when θ is distributed as a single 197 parameter distribution (e.g., exponential), φ would be a scalar number. The components of φ , which 198 are called hyper-parameters, are distributed accordingly to the hyper-prior distribution denoted by 199 $\pi_2(\varphi)$.

200 2.2 Generalized Linear Model

The GLMs represent a practical and more flexible extension of linear models. Indeed, a GLM allows a response variable to be correlated with the covariates through a given link function, as shown by Eq. 3 (Follmann & Wu, 1995).

204
$$g(Y) = \alpha_0 + \sum_{i=1}^n \sum_{j=1}^m \sum_{k=1}^r \alpha_i X_j^k$$
 (3)

where g(Y) represents the link function, while X_j are called covariates or predictors, or explanatory variables. Furthermore, α_0 identifies the intercept, α_i denotes the coefficients, k is an exponent integer, while n and m are the number of coefficients and predictors, respectively. Finally, Y is the response variable, which follows an exponential family distribution (e.g., normal, Poisson, or binomial) in a GLM.

For condition monitoring purposes, it is worthwhile mentioning that the response variable is a RI, e.g., the hazard rate or the meantime to failure, while the covariates are the monitored process variables, e.g., pressure or temperature. Thus, the link function defines the relationship between the RI (dependent variable) and the monitored process variables (independent variables).

214 2.3 Hierarchical Bayesian Regression

This paragraph summarises the procedure to perform HBR. The hyper-parameters of an HBR model are the intercept and the coefficients characterizing the link function. The prior distribution and the likelihood function are expressed through Eq. 4 and Eq. 5, respectively [46].

218
$$\pi_0(\theta) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} \dots \int_{-\infty}^{+\infty} \pi_1(\theta | \alpha_0, \alpha_1 \dots \alpha_n) \pi_2(\alpha_0, \alpha_1 \dots \alpha_n) \partial \alpha_0 \partial \alpha_1 \dots \partial \alpha_n$$
(4)

219
$$f(Y|\alpha_0, \alpha_1 \dots \alpha_n) = \int_{\Theta} f(Y|\theta) \pi_1(\theta|\alpha_0, \alpha_1 \dots \alpha_n) d\theta$$
(5)

where $\pi_1(\theta | \alpha_0, \alpha_1 \dots \alpha_n)$ and $\pi_2(\alpha_0, \alpha_1 \dots \alpha_n)$ are the first-stage prior and the hyper-prior, respectively. Through Bayes' Theorem (Eq. 1), the posterior distribution of the hyper-parameters is got by Eq. 6 (Zeger & Karim, 1991).

223
$$\pi_1(\alpha_0, \alpha_1 \dots \alpha_n | Y) =$$

$$224 \qquad \frac{\left[\int_{\Theta} f(Y|\theta)\pi_{1}(\theta|\alpha_{0},\alpha_{1}\dots\alpha_{n})d\theta\right]*\left[\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}\dots\int_{-\infty}^{+\infty}\pi_{1}(\theta|\alpha_{0},\alpha_{1}\dots\alpha_{n})\pi_{2}(\alpha_{0},\alpha_{1}\dots\alpha_{n})\partial\alpha_{0}\partial\alpha_{1}\dots\partial\alpha_{n}\right]}{\int_{\Theta}\left[\int_{\Theta} f(Y|\theta)\pi_{1}(\theta|\alpha_{0},\alpha_{1}\dots\alpha_{n})d\theta\right]*\left[\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}\dots\int_{-\infty}^{+\infty}\pi_{1}(\theta|\alpha_{0},\alpha_{1}\dots\alpha_{n})\pi_{2}(\alpha_{0},\alpha_{1}\dots\alpha_{n})\partial\alpha_{0}\partial\alpha_{1}\dots\partial\alpha_{n}\right]d\theta} \qquad (6)$$

In a Markov Chain Monte Carlo (MCMC) process, the posterior distribution is often estimated 225 numerically by Gibbs sampling by exploiting the conjugate prior. Given a certain likelihood, choosing 226 a conjugate prior makes the form of the posterior known. It is also possible to adopt a non-conjugate 227 prior distribution, but it will lead to higher mathematical complexity. Moreover, the property of the 228 conjugate prior allows the Gibbs algorithm to find the posterior distribution by first randomly 229 sampling from both the prior distribution (Eq. 4) and the likelihood function (Eq. 5), and subsequently 230 applying the Bayes' Theorem. Finally, the posterior predictive distribution for the unknown 231 232 parameter of interest (θ) is given by Eq. 7.

233
$$\pi(\theta|Y) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} \dots \int_{-\infty}^{+\infty} \pi_1(\theta|\alpha_0, \alpha_1 \dots \alpha_n) \pi_1(\alpha_0, \alpha_1 \dots \alpha_n|Y) \partial \alpha_0 \partial \alpha_1 \dots \partial \alpha_n$$
(7)

Accordingly, the posterior predictive distribution shown in Eq. 7 is obtained by MCMC via a sampling process of the joint posterior distributions of the hyper-parameters.

The remainder of this paper is organized as follows; Section 2 describes the methodology developed. Section 3 illustrates the implementation of the methodologies in the numerical example adopted as a case study, while Section 4 discusses the results. Finally, conclusions are presented in Section 5.

3. Developed methodology

Identifying a relationship between PVs and RIs represents a pivotal task in grasping the changing of reliability factors during operation. To this end, the primary goal of this paper is to develop a methodology that can correlate RIs and PVs (1) and estimate online reliability to schedule maintenance tasks (2). The sequence of the proposed four-stage framework is presented in Fig. 1.





Fig. 1 Developed framework for online reliability estimation with HBR and GLM.

246 *3.1. Stage 1: Experimental tests and data collection.*

In the proposed method, ALT with fixed PVs are performed on a given device (Step 1), and subsequently, Times To Failure (TTFs) are extracted (Step 2). Each ALT identifies a source of data that is later exploited to build the regression model.

250 3.2. Stage 2: Hierarchical Bayesian Regression

We chose different GLMs to test them on the acquired failure data (Step 3). Indeed, testing more than 251 one model can be practical since the relationship between the reliability indicator and the PVs is not 252 clear, and more than one valid relationship can exist. In the second case, the relationship that allows 253 modeling the data properly and simultaneously allows minimizing the complexity of the model must 254 be chosen. The choice of the models should be based on expert judgment, available physical 255 knowledge of the deterioration process, or historical data (BahooToroody et al., 2020b). After 256 choosing the models, they are tested separately and independently (Step 4). At first, prior distributions 257 are assigned to both the parameters of interest (Step 5) and the hyper-parameters (Step 6). The choice 258 of the prior distribution could be based on knowledge or could be non-informative. In the latter case, 259 the inference will be completely data-driven, since a non-informative prior is very diffusive and 260 spread over the variables' domains (e.g., a uniform prior). Besides, it is worthwhile mentioning that 261

choosing a conjugate prior is usually convenient for mathematical purposes since it allows to obtain a closed-mathematical solution. After setting the prior distributions, the HBR is performed to get the posterior distribution of the hyperparameters and the parameters of interest (Steps 7.1-7.2). Finally, the Bayesian p-value and the Deviance Information Criterion (DIC) are estimated (Steps 8-9). The Bayesian p-value determines the goodness of fit, while the DIC, given by Eq. 8, is exploited to compare distinct models.

268
$$DIC(\theta) = -2\log(f(Y|\theta))$$
 (8)

where $f(Y|\theta)$ is the likelihood function. The DIC is composed of two penalized functions: the first one considers the goodness of fit, while the second function evaluates the complexity of the model. Thus, assuming equal goodness of fit, the higher the complexity of the model, the higher the DIC.

272 3.3. Stage 3: Model selection

Since more models are tested on the available data, a criterion to pick one model over the others must 273 be chosen. The p-value compares the observations with the predicted values obtained through the 274 posterior distribution. In other words, the p-value determines how well the model replicates the data. 275 Particularly, a p-value lower than 0.05 denotes a model that generates much higher values than the 276 277 observed data, while a p-value higher than 0.95 is associated with a model which predicts much lower 278 values compared to the observations. Consequently, the mean p-value should be around 0.5 (Kelly & Smith, 2011), and in this study, every model whose mean p-value is less than 0.05 or higher than 0.95 279 280 is discarded (Step 10). Next, the remaining models are compared through the DIC; specifically, the model with the lowest DIC is selected (Step 11). 281

282 *3.4. Stage 4: Reliability estimation and maintenance scheduling*

Assuming that the considered device is working in standard operation, the fourth stage of the methodology is implemented. First, a reliability threshold is defined (Step 12). Indeed, critical equipment maintenance is usually scheduled as soon as a given reliability threshold is reached, rather than considering fixed indicators such as the Mean Time To Failure (MTTF). Subsequently, the PVs characterizing the selected GLM are monitored (Step 13), and the reliability of the component is computed at each time unit (Step 14). At last, maintenance is planned when the estimated reliability becomes lower than the aforementioned threshold (Step 15).

4. Results: Application of the methodology

- 291 To show the applicability of the method, we used a numerical example as a case study.
- *4.1. Stage 1: Experimental tests and data collection.*

We considered pressure and temperature as process variables for the ALT. Five distinct Operating 293 Conditions (OC) with five levels of pressure and two levels of temperature are evaluated. For each 294 295 operating condition, ten components are tested until failure (step 1), and the TTFs are extracted (step 296 2). This kind of ALT is usually called run-to-failure because the test is carried on until a failure occurs. However, the ALT may manage censored data since the tests are conducted for a limited period. Even 297 if censored TTFs are not considered for this numerical example, they could easily be included in the 298 analysis. It is also worthwhile mentioning that the number of operating conditions and components 299 to test should be chosen based on company policies, available knowledge, and expert judgment. 300 301 Considering as an example the study presented by Tucci et al. (2014), twenty-four components are tested in three distinct OCs, while in the work of Hamada et al. (2008) an example of forty 302 303 components and four OCs is reported. Given the aforementioned examples, the authors considered fifty components in five distinct OCs. The analysed OCs and the extracted TTFs are listed in Table 1 304 305 and Table 2, respectively.

306 Table 1 Considered OCs for the accelerated testing procedure.

PV	OC1	OC2	OC3	OC4	OC5
Pressure [bar]	8	9	10	11	12
Temperature [°C]	30	30	30	40	40

307

308 Table 2 TTFs (hours) extracted from the accelerated tests for each OC.

TTF	OC1	OC2	OC3	OC4	OC5
TTF1	113.61	107.20	95.91	71.21	67.65
TTF2	92.35	82.60	83.21	74.47	66.66
TTF3	104.15	93.18	93.31	94.89	43.98
TTF4	101.07	98.53	84.75	63.64	72.23
TTF5	112.17	102.64	89.14	68.73	75.53
TTF6	91.64	103.43	90.49	69.53	73.09
TTF7	118.12	94.57	87.37	81.56	67.07
TTF8	94.69	108.52	68.09	74.12	69.15
TTF9	99.41	83.72	56.95	63.54	71.44
TTF10	104.16	83.74	91.72	79.16	61.04

309

310 *4.2. Stage 2: Hierarchical Bayesian regression*

311 The third step of the methodology requires the specification of distinct models to test the data. The

312 TTF distribution should be chosen based on prior beliefs and knowledge of the failure process. In this

study, we assumed the TTF to follow a normal distribution, thus normal-normal regression models

are considered:

315
$$TTF \sim N(\mu, \sigma^2)$$
 (9)

Accordingly, the parameters of interest are the MTTF (μ) and the standard deviation (σ). Furthermore, the canonical link function for the normal-normal regression model is the identity function, as shown by Eq. 10.

319
$$\mu = MTTF = \alpha_0 + \sum_{i=1}^n \sum_{j=1}^m \sum_{k=1}^r \alpha_i X_j^k$$
(10)

Based on the previous paragraph, the Bayesian regression aims to determine the relationship between the MTTF and the PVs (i.e., pressure and temperature); therefore, two distinct models are developed, as shown in Eq. 11 and Eq. 12, respectively.

323
$$\mu = MTTF = a + b * Press + c * Temp$$
(11)

324
$$\mu = MTTF = a + b * Press \tag{12}$$

where a denotes the intercept, while b and c are the pressure and temperature coefficients, 325 respectively. In the first model, the influence of both pressure and temperature on MTTF is 326 327 investigated, while the second model addresses how pressure variations affect the MTTF. To conclude, the assignment of a prior distribution to each parameter of interest (step 5), a non-328 informative gamma prior is chosen for the standard deviation (Eq. 13). Indeed, the gamma prior is 329 the natural conjugate prior for the standard deviation, allowing for obtaining a closed-mathematical 330 solution. Moreover, choosing a non-informative prior allows comparing the results of HBM and other 331 estimation approaches such as MLE (D. L. Kelly & Smith, 2009). 332

333
$$\sigma \sim Gamma(0.0001, 0.0001)$$
 (13)

Next, the prior distributions for the hyper-parameters are defined (step 6). In the first model, there are three hyper-parameters (the intercept a, and the slopes b and c), while in the second model, there are two hyper-parameters (the intercept a and the slope b). Adopting non-informative priors is strongly recommended when enough data is available to avoid a powerful influence (of the prior choice) on the posterior distribution (Leoni et al., 2021). For each hyper-parameter, a diffusive normal prior is selected:

$$340 \quad a \sim N(0, 10^4) \tag{14}$$

$$341 b \sim N(0, 10^4) (15)$$

$$342 \quad c \sim N(0, 10^4) \tag{16}$$

The next phase is the development of the Bayesian regression, which is implemented through RJags. 343 To predict the posterior distributions (step 7), the MCMC sampling process is conducted with three 344 chains characterized by over-dispersed initial values. Considering over one chain is strongly 345 recommended to check the convergence of the process. Each chain is simulated with 10^5 iterations 346 preceded by 1,000 burn-in iterations. The statistical summaries of the posterior distributions of the 347 hyper-parameters are reported in Table 3 and Table 4 for the first and second models, respectively. 348 Fig. 2 illustrates the MCMC chains of the first model, while Fig. 3 shows the MCMC chains related 349 to the second model. 350

351 Table 3 Statistical summary of the posterior parameters of the first model

Parameter	Mean	Standard Deviation	2.5 percentile	97.5 percentile
а	178.023	10.3954	157.909	198.534
b	-9.0718	1.9926	-13.027	-5.234
с	-0.0752	0.5714	-1.147	1.072
sigma	10.0079	1.0569	8.193	12.326

352

353 Table 4 Statistical summary of the posterior parameters of the second model

Parameter	Mean	Standard Deviation	2.5 percentile	97.5 percentile
a	177.391	9.964	157.62	196.707
b	-9.2645	0.9866	-11.172	-7.307
sigma	9.9118	1.0352	8.135	12.188



356

Fig. 2 Trace plots (on the left) and predicted posterior distributions (on the right) for the unknown parameters of the first model.



Fig. 3 Trace plots (on the left) and predicted posterior distributions (on the right) for the unknown parameters of the second model.

Each color of Fig 2 and 3 denotes a different chain. The convergence of the second model is successful 359 since the three chains are well-mixed as depicted by the left graph of Fig. 3. For the first model (Fig. 360 2), the trace plots of the pressure (b) and the temperature (c) coefficient show a worse convergence 361 compared to the second model. However, for both models, the Gelman indexes related to the 362 predicted parameters are equal to 1 or very close to 1. The Gelman index estimates the ratio of the 363 within-chain variance and the between-chain variance. Thus, a Gelman index close to 1 indicates that 364 the variance within-chain and between-chain are similar, which is an indicator of convergence. 365 Furthermore, as revealed in Table 3, the influence of the temperature is much lower compared to the 366 367 relevance of the pressure. Indeed, the temperature coefficient is lower than the pressure coefficient in the first model. The aforementioned considerations could be useful to make an informed decision on 368 369 the model to pick, however, the following steps are required for a more in-depth and conscientious choice. Indeed, there are some scenarios characterized by equally suitable models when trace-plots, 370 Gelman index, and estimated parameters are the only considered factors. The validity of the 371 developed models is determined by estimating the Bayesian p-value (Step 8), while the choice of the 372 373 model is guided by the DIC (Step 9). For the first model, the mean p-value was equal to 0.4977, while the calculation revealed a mean p-value of 0.5004 for the second model. The first model is 374 375 characterized by a DIC equal to 374.6, while a DIC of 374.2 is associated with the second regression model. 376

377 *4.3. Stage 3: Model selection.*

The validity of both regression models is proved through the Bayesian p-value, which is close to 0.5, thus no model is discarded (Step 10). Furthermore, the DIC of the second model is slightly lower than the DIC associated with the first model. Accordingly, the second model is selected, and it is considered for the remaining part of this paper (Step 11).

To further prove the goodness of the model, the cost function illustrated by Eq. 17 is adopted.

383
$$Cost function = \frac{1}{2n} \sum_{i=1}^{n} (Pred_i - Obs_i)^2$$
[17]

where *n* denotes the number of observations, while $Pred_i$ and Obs_i are the *i*th prediction of the model and the *i*th observed value, respectively. The cost function is calculated for each value of the intercept (*a*) and the slope (*b*) within their respective 95% credible interval (listed in Table 4), using a discretization of 0.1. The cost function obtained is shown in Fig. 4, while the contour plot is illustrated in Fig. 5.





Fig. 5 Contour plot of the cost function. The red dot represents the minimum value.

The minimum value of the cost function is equal to 45.6 and it is located at (b,a) =393 (-9.472,179.52), which is pretty close to the mean value extracted through the HBR. 394

4.4. Stage 4: Reliability estimation and maintenance scheduling 395

Given a working component in a standard operating environment, the reliability decreases over time 396 397 because of a degradation process that is affected by the operating condition and the process variables. For this study, the reference threshold of the reliability is set equal to 0.4 (step 12), accordingly as 398 soon as the estimated reliability reaches this value, the operations are not regarded as safe and an 399 intervention is required. In other words, the threshold identifies the lowest acceptable value for the 400

estimated reliability. The reliability threshold should be chosen based on company policies, expert
judgments, guidelines, or regulations. considering the second regression model, the PV of interest is
the pressure monitored during the operation (Step 13). Fig. 6 shows the pressure observed during 500
hours of operation.



405

406

Fig. 6Monitored pressure during 500 hours of operation.

407 Next, the reliability is estimated considering a normal distribution, whose probability density function408 is given by Eq. 18.

409
$$f(t) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{t-\mu_t}{\sigma})^2}$$
 (18)

410 where μ_t is obtained by Eq. 12, considering the predicted parameters listed in Table 4 and the 411 monitored pressure for t. Thus, each time unit is associated with a different value of μ_t based on the 412 measured pressure. Since time is considered discrete, the unreliability is approximated, as shown by 413 Eq. 19.

414
$$F(T) = \sum_{t=1}^{T} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{t-\mu_t}{\sigma})^2}$$
(19)

The reliability of each time unit is subsequently estimated as the complement to one of the unreliability, as depicted by Eq. 20.

417
$$R(T) = 1 - \sum_{t=1}^{T} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{t-\mu_t}{\sigma})^2}$$
(20)

Following Equation 19, the reliability is estimated for each hour of the considered timespan (step 14).

419 Given the reliability threshold mentioned above, a maintenance task is planned when the estimated

reliability is less than 0.4 (step 15). Whenever a maintenance task is performed, the component is 420 replaced with a new one, considering a replacement "as good as new" (AGAN). Consequently, the 421 reliability is equal to 1 after the component is replaced. The estimated reliability and the scheduled 422 maintenance tasks during the considered time interval are illustrated in Fig. 7. The calculation depicts 423 three maintenance interventions: the first replacement is performed after 158 hours of operation, 424 while the second and third are carried out after 306 and 453 hours, respectively. In Fig. 7, the red 425 dotted lines represent a maintenance task (158, 306, and 453 hours), while the gray horizontal dotted 426 line represents the reliability threshold (0.4). 427







431 **5. Discussion**

429

432 *5.1 Alternative model*

The regression model with only the pressure as relevant PV is depicted as the best due to the lower DIC and the consistent Bayesian p-value. Moreover, the posterior mean value of the temperature coefficient related to the first model revealed less influence of the temperature on the reliability indicator. Since the pressure is regarded as the most influential PV, it is worth investigating another model characterized by a quadratic dependence of the MTTF regarding the pressure. The aforementioned model is illustrated by Eq. 21.

439
$$\mu = MTTF = a + b * Press + c * Press^2$$
(21)

- 440 By adopting the same prior distributions introduced in Section 3.2 the statistical summary reported
- 441 in Table 5 is got.

442 Table 5 Statistical summary of the posterior parameters associated with the model with quadratic pressure dependence.

Parameter	Mean	Standard Deviation	2.5 percentile	97.5 percentile
a	100.251	57.6577	-24.168	208.8459
b	6.5604	11.7032	-15.343	31.6898
c	-0.795	0.5866	-2.062	0.3025
sigma	10.0788	1.068	8.25	12.4237

The calculation revealed a mean p-value of 0.4985, which is an acceptable value. However, looking at the trace plot shown in Fig. 8, the convergence is not reached. Consequently, the developed model could not be accepted as valid and must be discarded.



447

448 Fig. 7 Trace plot of *c* (quadratic pressure coefficient), illustrating the absence of convergence for the developed regression model.

449 *5.2 Corrective maintenance and nonoperating time*

450 Fig. 5 is got considering no failure between two preventive maintenance tasks. However, failures could occur even if a CBM policy is implemented. During the non-operating time, the unreliability is 451 452 often considered constant; thus, it does not increase. Both CM and standby period could be easily added into the developed method. Indeed, whenever a failure occurs, a CM task is carried out, 453 restoring the AGAN condition (the reliability is reset to 1). Subsequently, the monitoring process is 454 reestablished until the occurrence of another failure or the preventive maintenance requirements are 455 met. Regarding the nonoperating time, let t be the instant of shutdown and t + n the time at which 456 the operations are re-started. To model the absence of degradation, the condition defined by Eq. 22 is 457 imposed. 458

459
$$F(t) = F(t+n)$$
 (22)

where F(t) is the estimated unreliability in t, while F(t + n) is the assigned unreliability for t + n. 460 Through Eq. 21, the unreliability is maintained constant, which is equal to constant reliability during 461 the non-operating period. As an example, a component operating under a normal TTF distribution 462 whose parameters are listed in Table 4 is considered. The history of the component state is shown in 463 Fig. 9, along with the recorded pressure. Table 6 reports a summary of the relevant events along with 464 their occurrence time. Before reliability drops below the threshold, a failure is observed after 130 465 hours of operation and a CM task is performed. Subsequently, the device operates until the estimated 466 reliability reaches the threshold value of 0.4, leading to a PM intervention after 279 hours of 467 operations. Next, another PM action is performed after 422 hours of operation. Finally, 552 hours 468 after the start of the operation, the pressure drops to 0, identifying a standby state. Accordingly, the 469 reliability of the component is kept equal to the reliability estimated during the last operating hour 470 until a new operating state is observed. Considering Fig. 9, a) reports the pressure and the reliability 471 till the CM is performed, while b) and c) displays the monitored pressure and the estimated reliability 472 till the first and the second PM task, respectively. Finally, d) illustrates the pressure and the reliability 473 until the end of the considered period. 474







478

Fig. 9 Integration of CM and non-operating time to the developed methodology for the presented example.

Table 6 List of the sequence of relevant events. PM denotes a PM task, while CM represents a CM task. Finally, SB identifies a transition to a standby state.

Time	130	279	422	552
Relevant event	СМ	PM	PM	SB

483 **6. Conclusions and future studies**

This paper presents a novel methodology capable of developing a regression model between PVs and 484 RIs through the exploitation of data extracted from ALT. The obtained regression function is then 485 used for conducting an online reliability estimation. In the framework developed, HBR and GLM 486 were integrated to determine the link function between the covariates and the dependent variable (that 487 is, RI). A normal-normal regression model was chosen, considering the MTTF as RI, while pressure 488 and temperature were chosen as relevant PVs. The HBR was implemented on data extracted from 489 five distinct operating conditions, while two distinct regression models were considered. Showing a 490 lower DIC, the model with only the pressure is selected as the best. Subsequently, the Bayesian 491 inference is used for the online reliability estimation, considering the pressure values detected during 492 493 500 working hours. Setting a reliability threshold equal to 0.4, three maintenance tasks after 158, 306, and 453 hours respectively emerged from the calculation. Finally, an extension with corrective 494 maintenance and nonoperating time is presented. 495

The presented approach could be adopted in any operational context where a manufacturer is testing its products through ALT. Indeed, a controlled operating environment is required to determine the relationship between the most relevant PVs and RI at first, and subsequently estimate the reliability during use. Consequently, the method could be useful both for the design and for the operating phases. During the design phase, the framework could assist the enterprises to test whether the reliability requirements are satisfied, while during the operating phase it could be helpful to optimize postsale services.

Among the limitations of the developed framework, it is worthwhile to mention the absence of 503 504 imperfect maintenance tasks and measurement errors arising from sensors. Thus, including these two 505 aspects in future developments could be relevant to make the methods more realistic. Indeed, any kind of maintenance task could be affected by process error, leading to partially restoring the life of 506 507 the maintained device. Additionally, measurement errors could influence the decision process related to maintenance planning. Another important limitation of the present work is that maintenance actions 508 509 are considered instantaneous (i.e., with no delay between the trigger and the start of the maintenance action). Future work could consider a maintenance delay related to logistics and resource issues, 510

anticipating the maintenance trigger based on the delay distribution and predictions regarding the values assumed by the PVs. Addressing these considerations will result in a prognostic approach. Furthermore, considering a real application could require some amendments to the framework, thus the authors are planning to test the developed framework on real industrial data. Finally, the comparison between this framework and other classic approaches could be useful to determine the advantages and disadvantages of each method, thus the authors are planning to work on this topic as well.

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