Reliability Engineering and System Safety 233 (2023) 109121

Contents lists available at ScienceDirect

Reliability Engineering and System Safety

journal homepage: www.elsevier.com/locate/ress

Prognosis of wear-out effect on of safety equipment reliability for nuclear power plants long-term safe operation

I. Martón [a,*], A.I. Sánchez [a], S. Carlos [b], R. Mullor [c], S. Martorell [b]

[a] Department of Statistics and Operational Research. MEDASEGI research group, Universitat Politècnica de València, Valencia, Spain
[b] Department of Chemical and Nuclear Engineering. MEDASEGI research group, Universitat Politècnica de València, Valencia, Spain
[c] Department of Mathematics, Universidad de Alicante, Alicante, Spain

ABSTRACT

To reach a Net Zero Emission scenario, on 1st January 2022 the European Union (EU) declared nuclear and gas as transitional activities under strict safety conditions. A central challenge is that many nuclear reactors in operation are close to or have reached their design life, so that, it is required to demonstrate the influence of equipment ageing on plant reliability will be kept under control in the plan extended lifetime. In this work a three-step methodology is proposed to obtain the time instants at which the failure rate behaviour changes (break points) and the most appropriate age-dependant reliability model to explicitly include the effects of ageing and maintenance. The methodology requires the reliability parameters estimation at each phase of the plant equipment lifetime, what is carried out by using the available Nuclear Power Plant (NPP) historical data, which is quite scarce. The methodology is applied to a motor operated valve of a NPP safety system. The results demonstrate the capability of the approach proposed to estimate and predict the component reliability in the plant extended lifetime depending on the maintenance policy implemented, being necessary to estimate an accurate age-dependant reliability model to support the decision-making process on equipment ageing management.

1. Introduction

On 1st January 2022, European Union (EU) declared nuclear and gas as transitional activities under strict conditions in order to achieve a Net Zero Emission scenario. These stringent conditions for nuclear energy imply that it has to fulfil with the highest standards of nuclear reliability and safety and also with the environmental safety requirements [1].

According to the IAEA's data, in the EU countries there are 104 nuclear reactors in operation, providing a total gross capacity of 149.53 GW(e). Most of the nuclear reactors in operation nowadays in EU, 95 out of 104, are Pressurized Light Water Reactor (PWR), which is the most widespread design around the world, is a robust and reliable technology which design follows the nuclear safety highest standards. However, as nuclear energy is present in Europe from the 1960, some of the plants are near of have already reach their lifetime. Thus, Fig. 1, shows the number of operational reactors in the EU by age, and it can be observed that most of them have been in operation 30 years or even more [2]. More specifically, 68.27% of the reactors are operating for more than 30 years, and 30.8% are in of the reactors are over 40 years old, what means that they have been approved an extended life to operate the plant beyond its design life, so they are in the Long-Term Operation (LTO).

Although, the operating performance of reactors between 30 and 40 years old is kept in an adequate level [3], the effect of ageing could affect the plant safety standards, as both may affect the plant risk level. So, it is necessary to re-evaluate the plant safety studies considering ageing effect in order to assure that the current operational reactors accomplish with all the nuclear safety requirements. That is, the plant risk level has to be re-evaluated to assure that is high enough to assure a safe plant operation.

In this context, the general objective of this paper is to develop a methodology that makes use of the available Nuclear Power Plants (NPP) historical data for the determination of the most appropriate age-dependant reliability model and parameters for each phase of the equipment lifetime considering ageing and imperfect maintenance. In particular this methodology provides (1) the determination of the time instants at which the component failure rate behaviour changes (break points), (2) the reliability parameters estimation at each phase of the plant equipment lifetime and (3) the possibility of forecast the component failure rate behaviour beyond the plant design life. So, the methodology developed can help in the diagnosis and prognosis of the ageing and maintenance effectiveness effect on the NPP active component's reliability. Thus, the novelty of this paper is the simultaneous estimation of the reliability model parameters considering the effect of imperfect maintenance, and the time at which the component reliability behaviour

* Corresponding author.
E-mail addresses: ismarllu@eio.upv.es (I. Martón), ismarllu@eio.upv.es (S. Martorell).

https://doi.org/10.1016/j.ress.2023.109121
Received 30 June 2022; Received in revised form 17 January 2023; Accepted 21 January 2023
Available online 25 January 2023

changes along its lifetime.

The paper is structured as follows. Section 2 makes an overview of the context of physical ageing management and reliability modelling and application. Section 3 introduces the material and methods, i.e. the fundamentals and models considered, the MLE technique and the estimation procedure. Section 4 presents the case of application of the methodology facing the estimation of the reliability parameters of a safety related component of a NPP. In Section 5 the results obtained in the application case are presented. Finally, section 6 exposes the concluding remarks of the study.

2. Ageing management context

Periodic Safety Reviews (PSR) are carried out at NPP with an aim at demonstrating that asset management programs are effective in controlling equipment ageing, in particular, of those Structures, Systems and Components (SSCs) critical for reactor safety [4]. This is of major interest as some SSCs may have entered a period of significant wear-out when they are close to or already within the long-term operation period. In addition, it is important to make an in-depth analysis of the evolution of wear-out and the role that equipment technical obsolescence can have on critical SSCs ageing, in order to assess their impact on operational safety. In this way it is possible to predict SSCs reliability behaviour and plan all the necessary maintenance activities to ensure that operational safety is kept under control in the long-term operation.

NPP safety assessment makes use of the Probabilistic Safety Analysis (PSA) which is periodically improved by updating equipment reliability models and data. In fact, such update consists of a new estimation of a constant failure rate based on the available failure data in the review period. This type of living PSA may not be sufficient to develop the safety review in an LTO context, as the assumption of a constant failure rate of safety equipment may not hold true, as equipment ageing or major degradation could start at some point in the LTO or even earlier. So, an advanced PSA is necessary to incorporate equipment reliability models, capable of forecasting the reliability evolution by explicitly considering ageing of components and testing and maintenance policies to be applied throughout the plant extended operating life. In addition, it is necessary to adapt the current parameter estimation methods to make them consistent with the proposed new models based on the historical failure and maintenance data available in the plant.

In this context, since ageing of components may not always start at its installation date, it is more convenient to estimate the parameters of age-dependant reliability models, subjected to imperfect maintenance, by considering a threshold for the starting point of equipment ageing. An age-dependant reliability model consists of a baseline reliability model that follows a certain probability distribution such as Weibull, exponential, linear, etc., which, in addition, integrates an imperfect maintenance model to account for the effects of maintenance effectiveness which should consider also ageing and obsolescence.

In the literature, there are many works that propose equipment reliability models that consider not only the baseline reliability model, but also the effect of ageing and maintenance and testing activities in an explicit way [5–9]. In addition, some of them consider several failures modes, being the most typical ones the by demand-caused failures and the standby-related failures [10–12]. In particular, in Ref. [10], an optimization of test and maintenance activities of a multi-component system with individually repairable components is performed considering two different failure modes. In Ref. [11] a Markov model is used to optimize a maintenance policy for components subjected to mutually dependant competing failure modes, in which equipment degradation is considered.

The most common models used to consider equipment ageing and maintenance effect into reliability models are the imperfect maintenance models, which consider age reduction according to the maintenance effectiveness which ranges between 0 and 1. Two models, i.e. Proportional Age Reduction (PAR) and Proportional Age Setback, are proposed in Ref. [13] as an intermediate situation between two extreme cases, the Good as New (GAN) model, in which the age of the equipment after each maintenance is restored to the initial time, and the Bad as Old (BAO) model, which assumes that the maintenance action has no effect on the age of the equipment.

Different approaches are proposed in the literature for estimating equipment reliability model parameters [14–19]. Some of them use a Bayesian approach to combine a generic probability density function with plant specific failure data [18,19]. Other studies obtain estimations of maintenance effectiveness and the most appropriate imperfect maintenance model using historical failure and maintenance data using maximum likelihood estimation (MLE) [14,15]. In Ref. [14], two types of failure modes are considered in the estimation process, failure by demand-caused failure, associated with a demand failure probability,

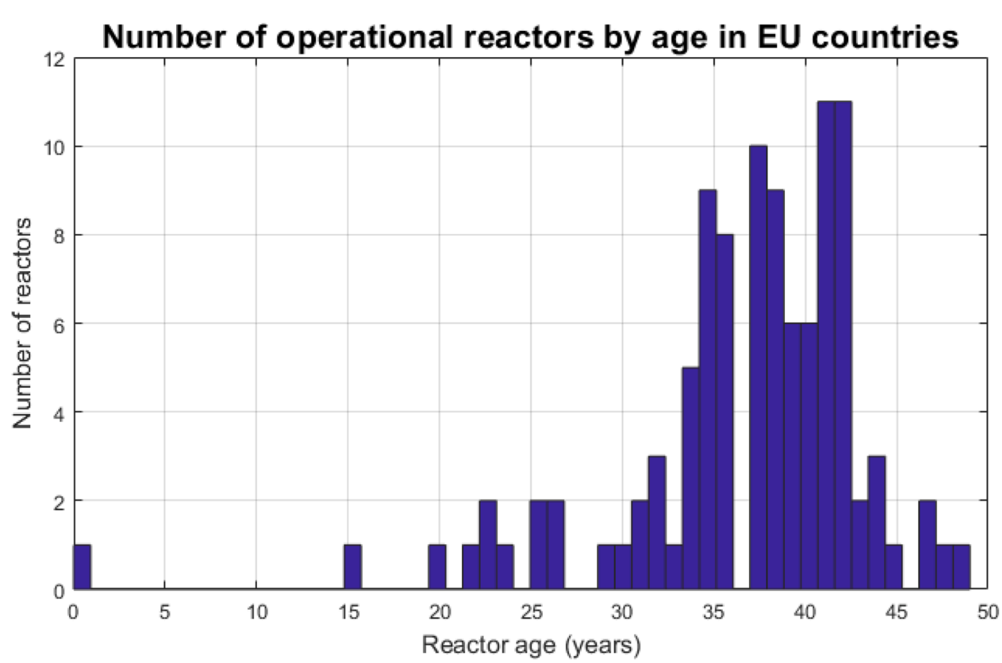

Fig. 1. Number of operational reactors by age in the EU (elaborated with data from PRIS [2]).

and standby-related failure, associated with a standby hazard function, and using a MLE approach the reliability model for both failure modes is estimated for safety components exposed to degradation by demand stress and ageing that undergo imperfect maintenance.

Others, for example, select the imperfect maintenance model (e.g. PAS or PAR) before estimating the parameters [15]. However, assuming a priori the maintenance model (BAO, GAN, PAS, PAR, etc.) before the estimation of the model parameters is not always necessary nor convenient for the decision-making process. An alternative option is to consider not only the baseline reliability model but also the imperfect maintenance model as part of the estimation process, what has been assumed in the present work.

A major problem in the customization the age-dependant reliability models used in risk-based decision-making application is the lack of or the little failure data available, due to the high equipment reliability and availability to guarantee the safety margins, together with the complexity of such models. Thus, age-dependant reliability models are composed of a large number of parameters related to reliability model (e.g. standby failure rate, per demand failure probability, e.g.) and imperfect maintenance model, (e.g. ageing rate, maintenance effectiveness, etc.). In some works machine learning approaches are used to assess the system's reliability, availability or remaining useful life in order to manage the number of variables in these models and to forecast the reliability evolution [20,21].

In addition, safety equipment at nuclear power plants has different failure patterns depending on the type of equipment. For example, in Ref. [22,23] six failure patterns of equipment reliability are identified, which can be characterized by considering the general behaviour of the bathtub curve for the h(t) (see Fig. 2, Pattern A), which represents the failure rate throughout the equipment useful life showing three phases: decreasing failure rate associated to infant failures, a constant failure rate associated to random failures and an increasing failure rate associated to ageing and degradation failures. Normally, this curve is associated with the Weibull distribution [24]. Weibull distribution can be approximated to a linear distribution to simplify the models when ageing grows slowly [24]. In the literature different approaches, extensions, and modifications of the Weibull distribution have been developed [25–28]. To reference a few works, in [25] and [26] use an additive Chen-Weibull distributions. Ref. [27] proposed an additive Weibull distribution by combining two Weibull distributions with cumulative distribution function. Ref. [28] a complete Bayesian analysis of new model named flexible additive Chen–Gompertz distribution. for censored and non-censored datasets and provide the Bayes estimators of the model parameters.

Fig. 2, Pattern B represents an equipment with no infant failures, with constant failure rate during most of its lifetime and with ageing-related failures departing from an onset threshold. This is the sort of equipment of interest in this paper. In addition, only the equipment failure mode associated with standby-related failures will be considered from now on.

Therefore, the challenge is twofold, the scarce failure data available must be used not only to estimate the large number of parameters together with the most appropriates baseline reliability and imperfect maintenance models for the particular phase, but also to determine the break points of the different phases in the behaviour of the particular equipment, i.e. the point at which the ageing period starts with an increasing trend of its standby-related failure rate.

3. Material and methods

3.1. Age-dependant reliability models

The Weibull distribution allows to model different patterns, for example, those shown in Fig. 2. In this figure, time t_1 and t_2 are the points at which there is a change of trend in the failure rate is observed. t_1 is the time at which the component changes from infant failure to random failure phase. In the random failure phase and up to t_2 the failure rate remains constant, normally modelled with an exponential failure distribution. From t_2 onwards, the failure rate is increasing and failures due to degradation or ageing begin. This last phase is usually modelled with a Weibull distribution.

In these types of studies is difficult to determine the start and end times of each phase. Sometimes, particularizations of the Weibull distribution are used, for example, Weibull can be approximated to a linear distribution, simplifying the mathematical model.

3.2. Baseline reliability model

In this work the Weibull distribution is considered to model the component reliability, as it is the most general one and, for this case of study, the most suitable one to determine the break points, that is the time at which the component reliability behaviour changes, and to implement the maintainability model, to explicitly consider age and imperfect maintenance. The functions that characterize the Weibull distribution and the relationships between them are the probability density function, the hazard function and the cumulative hazard function of the Weibull distribution given by Eqs. (1–3) respectively:

$$f(t) = \frac{\beta\ t^{\beta-1}}{\eta^{\beta}}\ exp\left(-\left(\frac{t}{\eta}\right)^{\beta}\right) \tag{1}$$

$$h(t) = \frac{\beta\ t^{\beta-1}}{\eta^{\beta}} \tag{2}$$

$$H(t) = \left(\frac{t}{\eta}\right)^{\beta} \tag{3}$$

where $\beta > 0$ and $\eta > 0$, are the shape parameter and scale parameter, respectively.

If the shape parameter of the Weibull distribution is equal to one, the failure rate is reduced to $h(t) = 1/\eta$ i.e. constant, therefore Weibull

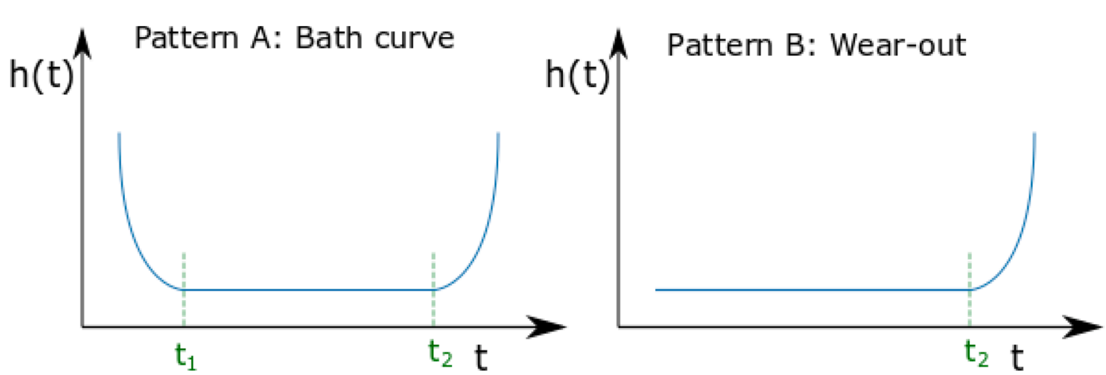

Fig. 2. Failure pattern of equipment (adapted from [24]).

distribution is simplified to an exponential distribution. If shape parameter is equal to 2, failure rate is equal to $h(t) = 2t/\eta^2$, being a linear positive function depending of chronological time, t. If the density probability function shape parameters take values equal to 1 or 2, it is ensured that the distribution obtained is exponential and linear, respectively.

3.3. Imperfect maintenance model

As mentioned above, the effect of maintenance on the component age will be considered using imperfect maintenance models. The Proportional Age Reduction (PAR) and Proportional Age Set-back (PAS) models are considered as they represent more adequately than the traditional Bad As Old (BAO) and Good As New (GAN) models, the influence that maintenance has on the equipment's ageing.

PAR Model [13] models the reduction in the increase in the age acquired since the last maintenance, based on the expression:

$$w^{+}_{m-1} = t - \varepsilon\tau_{m-1} \tag{4}$$

Whereas PAS model [13] models the total reduction in the age of the component by the following expression:

$$w^{+}_{m-1} = t - \sum_{k=0}^{m-2}(1-\varepsilon)^k\ \varepsilon\ \tau_{m-k-1} \tag{5}$$

Where w^{+}_{m-1} is the age after (m-1)-maintenance, t is the chronological time, τ_i is the time which m-1 maintenance is performed and ε is the effectiveness of preventive maintenance that is ranged between 0 and 1 and it is considered as a constant.

Substituting time for age in the expressions of failure cumulative failure rate, Eqs. (2) and (3), age-dependant reliability models are obtained which models include the effect of maintenance particularized for Weibull distribution, following expressions are obtained.

Weibull-PAR model

$$h_m(t) = \frac{\beta}{\eta^\beta}(t - \varepsilon\tau_{m-1})^{\beta-1} + \lambda_0 \tag{6}$$

$$H_m(t) = \frac{1}{\eta^\beta}(t - \varepsilon\tau_{m-1})^{\beta} + \lambda_0(t - \varepsilon\tau_{m-1}) \tag{7}$$

Weibull-PAS model

$$h_m(t) = \frac{\beta}{\eta^\beta}\left(t - \sum_{k=0}^{m-2}(1-\varepsilon)^k\ \varepsilon\ \tau_{m-1}\right)^{\beta-1} + \lambda_0 \tag{8}$$

$$H_m(t) = \frac{1}{\eta^\beta}\left(t - \sum_{k=0}^{m-2}(1-\varepsilon)^k\ \varepsilon\ \tau_{m-1}\right)^{\beta} + \lambda_0\left(t - \sum_{k=0}^{m-2}(1-\varepsilon)^k\ \varepsilon\ \tau_{m-1}\right) \tag{9}$$

being λ_0 the residual failure rate.

Eqs. (6) to (9) can be simplified to a linear distribution considering shape parameter equal to 2, obtaining the following expressions:

Linear-PAR model

$$h_m(t) = \alpha(t - \varepsilon\tau_{m-1}) + \lambda_0 \tag{10}$$

$$H_m(t) = \frac{\alpha}{2}(t - \varepsilon\tau_{m-1})^2 + \lambda_0(t - \varepsilon\tau_{m-1}) \tag{11}$$

Linear-PAS model

$$h_m(t) = \alpha\left(t - \sum_{k=0}^{m-2}(1-\varepsilon)^k\ \varepsilon\ \tau_{m-k-1}\right) + \lambda_0 \tag{12}$$

$$H_m(t) = \frac{\alpha}{2}\left(t - \sum_{k=0}^{m-2}(1-\varepsilon)^k\ \varepsilon\ \tau_{m-k-1}\right)^2 + \lambda_0\left(t - \sum_{k=0}^{m-2}(1-\varepsilon)^k\ \varepsilon\ \tau_{m-k-1}\right) \tag{13}$$

being α the linear ageing rate.

3.4. Maximum likelihood estimation (MLE)

The simultaneous estimation of the parameters of the imperfect maintenance models, considering ageing and imperfect maintenance effect, is performed by the MLE. For a given model and a set of observed data, the likelihood function, L, is defined as the product of occurrence probabilities, p_i, of the observed events, as a function of the vector of model parameters, ξ.

$$L(\xi|model,\ sample) = \prod_{event} p_i \tag{14}$$

This expression can be applied to reliability models with imperfect maintenance by relating density functions with failure probabilities and considering reliability functions to model probabilities after each maintenance activity. Since the failures observed in each component are dependant events, the density function to be used should be conditioned to the interval in which each event is observed. Thus, the failure rate is obtained and the general expression of the likelihood function in reliability models is given by

$$L(\xi|model,\ sample) = \prod_{failure} h(t) \times \prod_{maintenance} \exp(-H(t)) \tag{15}$$

where the expressions corresponding to *h(t)* y *H(t)* are obtained using Eqs. (6) to (13).

MLE provides estimators of the parameters included in the reliability models for repairable equipment with imperfect maintenance. The maximum likelihood estimates of these parameters are the values that maximize the likelihood function, i.e., maximize the probability of occurrence of the observed events.

Let $r_{p,m}$ the number of failures observed in component p, during maintenance interval m, failures occurring at times $t_{p,m_1},\ t_{p,m_2},\ldots$, and let $\tau_{p,m}$ the instant at which maintenance m is performed on component p. The likelihood function for P identical components of a repairable equipment under imperfect preventive maintenance is be given by

$$L(\xi) = \prod_{p=1}^{P}\left\{\prod_{m=1}^{M_p+1}\left[\prod_{j=1}^{r_{p,m}} h_{p,m}(t_{p,mj})\cdot exp\left(-\sum_{m=1}^{M_p+1}H_{p,m}(\tau_{p,m}) - H_{M_p+1}\left(\tau^*_p\right)\right)\right]\right\} \tag{16}$$

where ξ is the array of unknown parameters, and therefore the objective of the estimation process, which in the case of a Weibull distribution will be given by (β,η,ε), the shape and scale parameters of the Weibull failure distribution and the maintenance effectiveness, respectively. If a linear model is considered the array of the parameters is simplified to (α, ε), being α the linear ageing rate. For each component p, M_p is the number of maintenance activities performed during the observation period τ^*_p, being $h_{p,m}(t)$, $H_{p,m}(t)$ y $H_{p,m}(\tau)$ the induced failure rate and the cumulative failure rate in period m, respectively, and $H_{M_p+1}(\tau^*_p)$ the cumulative failure rate in the censoring time τ^*_p.

Since the natural logarithm is a monotonically increasing function, the likelihood function and its logarithm will reach the maximum at the same values of the parameters, so the function usually used in this context is the logarithm of the likelihood function. By taking logarithms in the Eq. (16) the expression of the logarithm of the likelihood function for repairable equipment under imperfect maintenance is given by

$$\log L(\xi) = \sum_{p=1}^{P}\left\{\sum_{m=1}^{M_p+1}\sum_{j=1}^{r_{p,m}}\log\left(h_{p,m}(t_{p,m,j})\right) - \sum_{m=1}^{M_p}H_{p,m}(\tau_{p,m}) - H_{M_p+1}\left(\tau^*_p\right)\right\} \tag{17}$$

MLE method also provides information about the estimated parameter variability using the Fisher information matrix, which is defined as the opposite of the matrix of second partial derivatives, so, for each model considered, the variance-covariance matrix as the inverse of the Fisher information matrix is obtained. The Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC) are considered to select best estimation models. Ref. [29,30], propose the following models

$$AIC = -2\log(L) + 2k \tag{18}$$

$$BIC = -2\log(L) + k\log(n) \tag{19}$$

where L is value of the likelihood function, k represents the number of estimated parameters and n the sample size used for the estimation. A more detailed description of AIC and BIC can be found in Ref. [31].

3.5. Estimation procedure

The methodology proposed for estimating the parameters of the models are based on a 3-step approach, which is represented in Fig. 3. As shown in this figure, the reliability and maintenance parameters estimation in the ageing phase requires a previous determination of the time instants where the random failure phase, t_1, and the ageing phase, t_2, start, as well as the estimation of the residual failure rate in the random failure period. The methodology is described in detail below considering an equipment that follows Pattern B in Fig. 2, with no infant failures, assuming constant failure rate during most of its lifetime and with ageing-related failures departing from an onset threshold, which is the sort of equipment of interest in this paper.

Step 1. Estimation of t_1 and t_2

Based on the proposals made in studies in the literature [22,32], this stage consists of identifying the time instants, i.e. t_1 and t_2, in which a change in the behaviour of *h(t)* occurs, in order to estimate the interval of different phases (infant failures, random failures and ageing) of the failure rate.

The identification t_1 and t_2 has been performed using the cumulative hazard function by the Nelson-Aalen estimator.

Let $X_1, X_2, .., X_n$ the order statistics associated to $T_1, T_2, \ldots T_n$, then the empirical hazard function is [32]:

$$\widehat{H_n} = \sum_{i:Z_{i\le t}} \frac{\delta_i}{n-i+1} \tag{20}$$

Once the failure rate is estimated, the instants of trend change are estimated using joint point regression [33]. This model is a piecewise linear regression model that characterizes the trend behaviour of data by identifying the significant points where changes occur. This is carried out by detecting the points and their locations in the data range.

Step 2. Estimation of the residual failure rate *(λ_0)*

In this step the residual failure rate (λ_0) corresponding to the exponential distribution of random failures is determined. Thus, once t_2 has been determined, the random failure phase ends, and λ_0 is estimated as the inverse of t_2. At this phase it is important to note that the estimated value of λ_0 is calculated by considering implicitly both, linear ageing rate (α) of the equipment and maintenance effectiveness (ε).

Step 3. Estimation of the Weibull/lineal parameters in the wear-out period considering the residual failure rate and a PAS/PAR imperfect maintenance model.

Once the starting time of the ageing phase, t_2, and the residual failure rate, λ_0, have been identified in steps 1 and 2, the reliability and maintenance parameters corresponding to the ageing period are estimated. One aspect that differentiates the parameter estimation process in the ageing phase, with respect to the phase of random failures, is that in this phase it is absolutely necessary to consider explicitly the effect of both ageing (α) and imperfect preventive maintenance (ε and PAS/PAR model).

From the estimates obtained in the previous step and the failure rate and cumulative failure rate equations Eqs. (6) to (13) corresponding to the PAR and PAS models considering a Weibull and lineal distribution and the logarithm of the likelihood function (Eq. (17)), the parameters of the failure distribution (maintenance effectiveness and the imperfect maintenance model and its parameters) are estimated.

In the estimation process, the variance-covariance matrix corresponding to the estimated parameters is obtained. This matrix allows the construction of confidence intervals that will allow us to analyse whether there are significant differences between the parameters of each model. The selection of the final model amongst the different reliability models, e.g., linear and Weibull, and maintenance models, PAR and PAS, proposed is made from the Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC) defined in Eqs. (18) and (19).

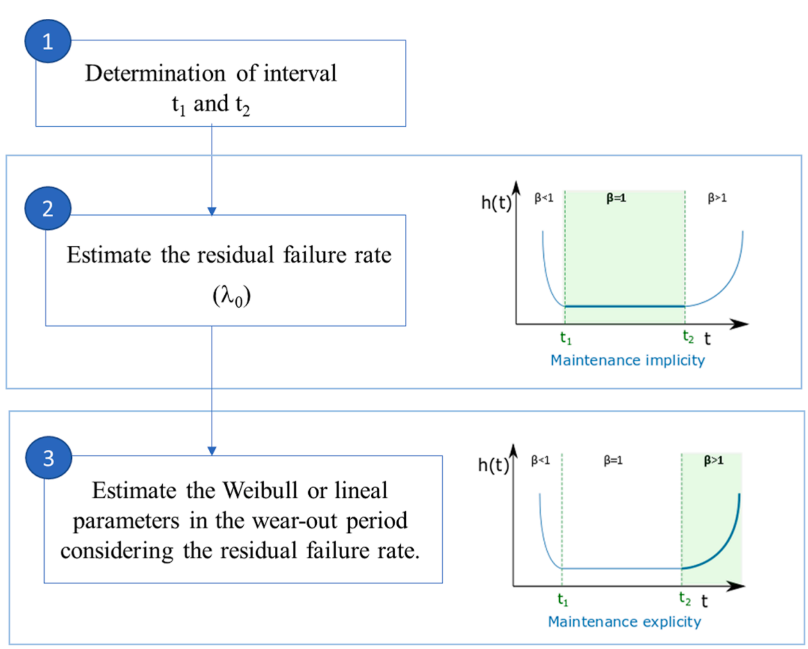

Fig. 3. Methodology proposed for estimating the parameters of the failure distribution.

4. Case study

4.1. Problem description

The study is focused on one type of safety equipment in a nuclear power plant. Specifically, the type of equipment analysed is a motor-operated safety valve. Historical failure and corrective and preventive maintenance data has been collected from the nuclear power plant for eight identical motor-operated safety valves. The dataset contains all failures and preventive maintenance activities recorded during an observation period of 17 years.

After studying the failure history data, only those failures related to the failure mode of the equipment on standby were selected. A total of 56 standby-related failures were selected over the period analysed, with a total of 138 maintenance activities having been carried out regularly on the equipment considered in the same period. Fig. 4 is a graphical representation of the failure times in the period considered, which allows an approximate visualization of the periods corresponding to the stages of infantile failures (up to t_1), random failures (from t_1 to t_2) and ageing (after t_2). Thus, a considerable accumulation of failures is observed at the beginning of the observation time, then the failures start to space out and become apparently evenly distributed, and finally, a period is observed in which failures start to appear more frequently towards the end of the observation time. However, it is not straightforward to precisely determine the times t_1 and t_2 in this way.

The following subsections follow the methodology proposed in the second section to determine precisely both the breakpoints of the different intervals and the best possible estimate of the age-dependant reliability model for the type of moto-operated safety valve, differentiating between the period of random failures and the period where the effect of ageing and maintenance must be explicitly considered. These reliability models will correspond to the standby-related failures of the equipment.

4.2. Determination of the t_1 and t_2 breakpoints

Firstly, the estimation of t_1 and t_2 is obtained using the approach described in the step 1 of the methodology. Fig. 5 shows a graphical representation of the cumulative mean function plot (red dots) using the Nelson-Allen method. From this distribution, it is possible to determine t_1 and t_2 using a segmented regression method, which is also represented in this Fig. 5, where it can be observed that the t_1 and t_2 breakpoints corresponds to 458 days (1.25 years) and 5051 days (13.83 years) respectively.

4.3. Determination of the λ_0 parameter of the exponential distribution of random failures

Next, the residual failure rate of the standby-related failures corresponding to the random distribution of failures in the period $[t_1, t_2]$ is estimated according to the step 2 of the methodology. The most important assumptions are the following. Only the failures included in this period $[t_1, t_2]$ are considered, there is no an explicit ageing effect so, there is no sense to account for imperfect maintenance models. Therefore, only the baseline reliability function is considered in this period assuming an exponential distribution of failures. The estimated value for the residual failure rate of the standby-related failures, λ_0, has been 1.98E-04 days^{-1} (8.25E-06 hr^{-1}).

4.4. Determination of age-dependant reliability distribution for the wear-out period

The next step is the estimation of the parameters of the age-dependant model of standby-related failures in the ageing phase following step 3 of the methodology and using the results obtained in the previous sections (see Fig. 3). The most important assumptions are the following. Only the failures included in the wear-out period are considered, i.e. $[t_2, \infty[$. In this phase, the effect of ageing and maintenance activities are explicitly considered in the baseline reliability and imperfect maintenance models. Thus, in this step, the most appropriate models (PAR or PAS, and Weibull or Linear failure distribution) and corresponding parameters (ageing, scale and shape factors, maintenance effectiveness, …) must be estimated. In this process, the value t_2 and the estimated residual failure rate, λ_0, of the random failure period are considered.

Table (1) shows the estimated values of the different parameters. As can be observed, all the results obtained are quite similar but, taking into account that the number of parameters in each model is different, it is more appropriate to use the AIC for model selection. Thus, the best estimation result obtained considering AIC criterion corresponds to the Weibull-PAS and Weibull-PAR models with maintenance effectiveness equal to 1. Then, there is no difference between the parameter estimation results of the reference Weibull reliability model with the imperfect maintenance models PAS and PAR, which is justified because both imperfect maintenance models provide the same results when the maintenance effectiveness is equal to 1.

Therefore, it is not necessary to assume a priori an imperfect maintenance model PAS or PAR because the proposed procedure in step 3 allows to find the most appropriated model together with the estimation of the parameters based on the AIC criterion. In this case, the a priori selection of the imperfect maintenance model would not have any influence on the result of the best estimate of step 3. However, this conclusion cannot be generalized, as when the maintenance effectiveness is less than 1, the consideration of different models does not provide the same results.

Table (1) also shows the confidence intervals (CI) of the parameter estimates. In particular, the CI for maintenance effectiveness ranges in the interval [0.90, 1]. For this reason, it has been considered interesting to carry out a sensitivity study on the incidence of selecting a PAR or PAS model in the parameter estimation when the effectiveness value is less than 1. For this purpose, the MLE method in step 3 of the methodology has been applied assuming a maintenance effectiveness equal to 0.9 and that imperfect maintenance follows a PAR and PAS type model respectively. Thus, the base reliability model and the associated parameters that best fit the available data have been re-estimated. The results are shown in Table (2), where it can be observed that the best estimation based on the AIC criterion corresponds to the Weibull-PAS model with maintenance effectiveness equal to 0.9. This result confirms that it not necessary to assume a priori an imperfect maintenance model, moreover it reveals that it is not convenient as it may lead to estimate an age-dependant reliability model that does not fit the historical data.

Fig. 6 presents the evolution of the time-dependant evolution of the

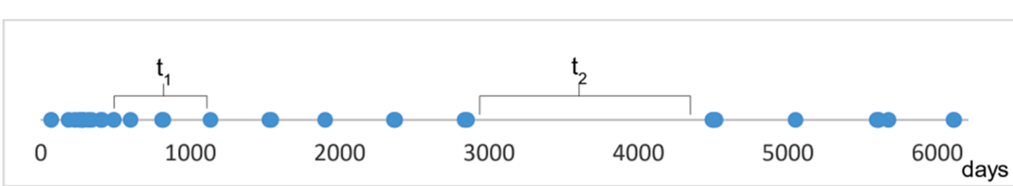

Fig. 4. Failure distribution over the observation period (time in days).

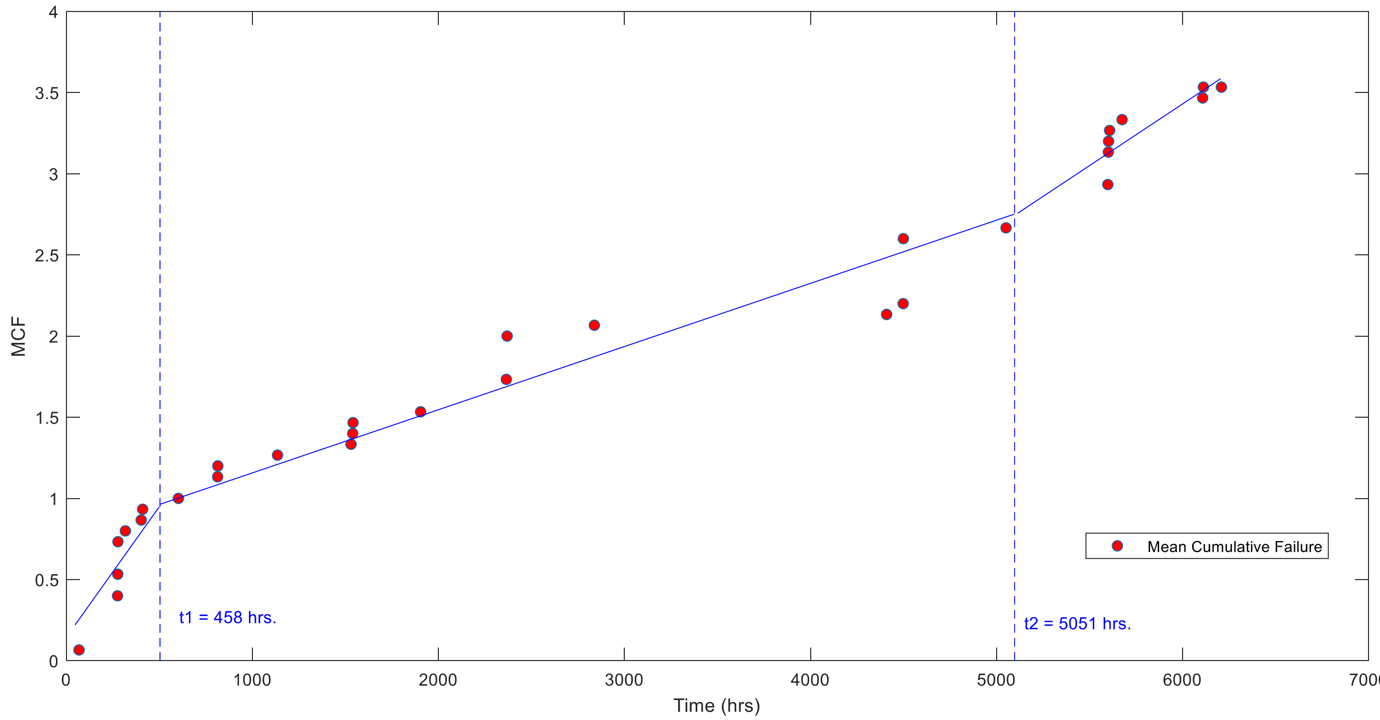

Fig. 5. Representation of cumulative mean function plot.

Table (1)
Results of the age-dependant standby-related failure rate for the wear-out period.

Reliability model	α	CI (α) (* E-06)	β	95% CI (β)	η	CI (η)	IM model	ε	95% CI (ε)	AIC
Lineal	1.68 E-06	[1.65, 1.71]					PAR	1	[0.90, 1]	100.62
Lineal	1.68 E-06	[1.65, 1.71]					PAS	1	[0.90, 1]	100.62
Weibull			**4.47**	**[4.21, 4.73]**	**806.75**	**[781.91, 831.59]**	**PAR**	**1**	**[0.90, 1]**	**98.89**
Weibull			**4.47**	**[4.21, 4.73]**	**806.75**	**[781.91, 831.59]**	**PAS**	**1**	**[0.90, 1]**	**98.89**

Table (2)
Estimation of the parameters of the reliability models considered ε equal to 0.90.

Reliability model	α	95% CI (α) (* E-06)	β	95% CI (β)	η	95% CI (η)	IM model	ε	AIC
Lineal	1.55 E-06	[1.52, 1.58]					PAR	0.9	101.64
Lineal	1.59 E-06	[1.56, 1.62]					PAS	0.9	101.28
Weibull			4.62	[4.30, 4.94]	825.14	[807.37, 842.91]	PAR	0.9	100.22
Weibull			**4.60**	**[4.32, 4.88]**	**822.51**	**[802.21, 842.81]**	**PAS**	**0.9**	**99.85**

standby-related failure rate for a motor-operated valve considering a Weibull reliability model for different imperfect maintenance considerations.

As shown in this figure, diagnosis phase comprises the time from the component installation to $t_3 = 17$ years (7200 days) and the prognosis phase considers the period from t_3 to beyond. And, it can be observed that the behaviour of the standby-related failure rate is different only for the wear-out period depending on the imperfect maintenance model selected. Thus, the red curve corresponds to a Weibull reliability model with imperfect maintenance PAR/PAS and maintenance effectiveness equal to one, PAS/PAR (1). The second and third cases correspond to a Weibull reliability model with PAR and PAS imperfect maintenance model, respectively, and maintenance effectiveness equal to 0.9 for both (grey curve for PAR(0.9) and blue curve for PAS(0.9)).

From the analysis of Fig. 6 different conclusions can be drawn. In the wear-out period [13.83, 17] years, where the three models have been estimated, there is not much difference in the behaviour of the three curves, although the PAR(0.9) model predicts the highest λ(t) results. In the prognosis phase, if one wants to analyse the failure rate up to the end of the plant design life, $t_4 = 40$ years, what corresponds to the period [17, 40] years, the PAS/PAR(1) and PAS(0.9) models show very similar predictions, however, the PAR(0.9) model predicts a very large increase in λ(t). In conclusion, it appears that PAS/PAR(1), provides a better prediction of λ(t) behaviour. A priori PAR(0.9) could have been considered a good estimate in the diagnosis period, but this leads, in the prognosis period, to a λ(t) behaviour very far from PAS/PAR(1), which is the best estimate found (see Table 2).

5. Concluding remarks

In order to help in achieving Net Zero Emission scenario, EU has declared nuclear energy as transitional activity under strict safety

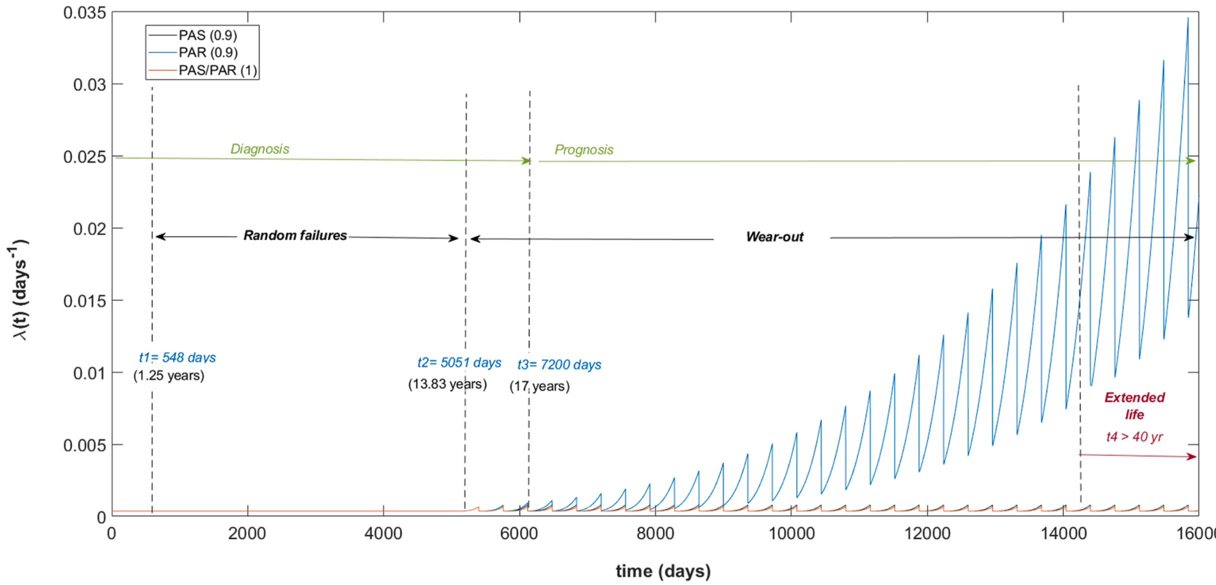

Fig. 6. Time-dependant evolution of the standby-related failure rate of the motor-operated valve under several behaviours.

conditions. Most of nuclear reactors in operation in EU are close to or have reached 30 or 40 years, what is their design life, so the effect of ageing influence on equipment reliability has to be assessed to guarantee the plant safety standards.

In the paper a 3-step approach methodology, based on MLE, to estimate the reliability parameters and maintenance models is proposed. The first step of the methodology consists of determining the time at which failure rate behaviour changes, and then the estimation of the failure rate is undertaken. This methodology also provides the best maintenance model to simulate the component behaviour.

This methodology has been applied to a motor operated valve, which is a NPP safety system equipment. The application case has demonstrated the capability of the approach proposed, no matter the scarce failure data available, in particular, in the wear-out phase of the equipment lifetime. Moreover, the methodology can cope with the complexity and large number of parameters to be estimated in an integrated way, and with the selection of the most appropriated baseline reliability and imperfect maintenance model.

Once the model and parameters are estimated, based on the available historical data, it is possible to perform a prognosis of the failure rate behaviour to be used in the life extension decision making process. The results demonstrate that maintenance is very effective ($\varepsilon = 1$) and perfectly controls the failure rate degradation. This conclusion should be confirmed in the future with greater operational experience plant, for example 30 to 40 years beyond its design life, by repeating the current procedure for the wear-out stage. Furthermore, physical and non-physical ageing problems may arise, leading to a reduction in maintenance effectiveness and possible acceleration of equipment degradation, which should be reflected in the re-estimation of the models and data proposed. Therefore, it is highly recommended to carry out this study periodically, in particular, for the wear-out period.

Finally, the case study has shown that, not only is it not necessary to assume a priori an imperfect maintenance model, PAS or PAR, but it is also not desirable, as it may lead to an inaccurate estimation of age-dependant reliability model, unable to provide an adequate prognosis of the motor-operated valve failure rate evolution to support accurate and plant-specific decision-making process in the context of long-term operation, even beyond the design life.

Thus, the methodology presented may be used by NPPs operators and regulatory bodies in order to assist in the operation safety factors self-assessment, to analyse aspects such as ageing and obsolescence, re-planning the maintenance plans and surveillance requirements, and in the risk impact evaluation.

CRediT authorship contribution statement

I. Martón: Methodology, Data curation, Writing – original draft, Writing – review & editing. **A.I. Sánchez:** Conceptualization, Methodology, Data curation, Investigation, Project administration. **S. Carlos:** Writing – original draft, Writing – review & editing. **R. Mullor:** Methodology, Data curation, Validation. **S. Martorell:** Conceptualization, Formal analysis, Data curation, Methodology, Validation, Writing – review & editing.

Declaration of Competing Interest

All the authors declare that they no established conflicting financial interests or personal relationship that may have influenced the research presented in this paper.

Data availability

The data that has been used is confidential.

Acknowledgement

Grant PID2019-110590RB-I00 funded by MCIN/AEI/10.13039/501100011033 “ERDF A way of making Europe”.

References

[1] Amending Delegated Regulation (EU) 2021/2139 as regards economic activities in certain energy sectors and Delegated Regulation (EU) 2021/2178 as regards specific public disclosures for those economic activities. Annex 1. C(2022) 631 final. Brussels: European Commission; 2022.
[2] Nuclear power reactors in the world iaea-rds-2/41, international atomic energy agency. Vienna: International Atomic Energy Agency (IAEA); 2021. ISBN 978-92-0-124421-5.
[3] World Association of Nuclear Operators (WANO). World nuclear performance report 2021. World Nuclear Association; 2021. Report No. 2021/003.
[4] Ageing management and development of a programme for long-term operation of nuclear power plants. Viena: draft safety guide DS 485 2017.
[5] Kančev MČ, Gjorgiev B. Development and application of a living probabilistic safety assessment tool: multi-objective multi-dimensional optimization of surveillance requirements in NPPs considering their ageing. Reliab Eng Syst Saf 2014;131:135–47. https://doi.org/10.1016/j.ress.2014.06.009.

[6] Kančev D, Gjorgiev B, Volkanovski A. M. Čepin Time-dependent unavailability of equipment in an ageing NPP: sensitivity study of a developed model. Reliab Eng Syst Saf 2016;148:11–20. https://doi.org/10.1016/j.ress.2015.11.014.
[7] Kim H, Kim JT. G. Heo Failure rate updates using condition-based prognostics in probabilistic safety assessments. Reliab Eng Syst Saf 2018;175:225–33. https://doi.org/10.1016/j.ress.2018.03.022.
[8] Martón I, Sánchez AI, Martorell S. Ageing PSA incorporating effectiveness of maintenance and testing. Reliab Eng Syst Saf 2015;139:131–40.
[9] Martorell P, Martón I, Sánchez AI, Martorell S. Unavailability model for demand-caused failures of safety components addressing degradation by demand-induced stress, maintenance effectiveness and test efficiency. Reliab Eng Syst Saf Reliab Eng Syst Saf 2017;68:18–27.
[10] Martón I, Martorell P, Mullor R, Sánchez A, Martorell S. Optimization of test and maintenance of ageing components consisting of multiple items and addressing effectiveness. Reliab Eng Syst. Saf. 2016;53:151–8.
[11] Jingjing W, Rui Z, Tianran L. Maintenance modeling for balanced systems subject to two competing failure modes. Reliab Eng Syst. Saf. 2022;225:108637. https://doi.org/10.1016/j.ress.2022.108637. ISSN 0951-8320.
[12] Cheng Y, Wei Y, Liao H. Optimal sampling-based sequential inspection and maintenance plans for a heterogeneous product with competing failure modes. Reliab Eng Syst. Saf. 2022;218:108181. https://doi.org/10.1016/j.ress.2021.108181. Part B.
[13] Martorell S, Sanchez A, Serradell V. Age-dependent reliability model considering effects of maintenance and working conditions. Reliab Eng Syst. Saf. 1999;64:19–31.
[14] Martorell S, Martorell P, Sánchez AI, Mullor R, Martón I. Parameter estimation of a reliability model of demand-caused and stand-by related failures of safety components exposed to degradation by demand stress and ageing that undergo imperfect maintenance. Math Probl Eng 2017. Article ID 7042453.
[15] Mullor R, Mulero J, Trottini M. A modelling approach to optimal imperfect maintenance of repairable equipment with multiple failure modes. Comput Ind Eng 2019;128:24–31.
[16] Chunling L., Lijuan S., Ancha X., Modelling and estimation of system reliability under dynamic operating environments and lifetime ordering constraints, Reliab Eng Syst. Saf., Volume 218, Part A, 2022, 108136, ISSN 0951-8320, doi:10.1016/j.ress.2021.108136.
[17] Éder SB, Vera L, Tomazella D, Ferreirad PH. Statistical modeling and reliability analysis of multiple repairable systems with dependent failure times under perfect repair. Reliab Eng Syst. Saf. 2022;222:108375. https://doi.org/10.1016/j.ress.2022.108375. ISSN 0951-8320.
[18] Shuto S, Amemiya T. Sequential Bayesian inference for Weibull distribution parameters with initial hyperparameter optimization for system reliability estimation. Reliab Eng Syst. Saf. 2022;224:108516. https://doi.org/10.1016/j.ress.2022.108516.
[19] Betz Wolfgang, Papaioannou Iason, Straub Daniel. Bayesian post-processing of Monte Carlo simulation in reliability analysis. Reliab Eng Syst. Saf. 2022;227:108731. https://doi.org/10.1016/j.ress.2022.108731.
[20] Shouman MA, Saber AS, Shaat MK, Torkey A. A hybrid machine learning model for reliability evaluation of the reactor protection system. Alexandria Eng. J. 2022;61(9):6797–809. https://doi.org/10.1016/j.aej.2021.12.026.
[21] Xu Y, Kohtz S, Boakye J, Gardoni P, Wang P. Physics-informed machine learning for reliability and systems safety applications: state of the art and challenges. Reliab Eng Syst. Saf. 2023;230:108900. https://doi.org/10.1016/j.ress.2022.108900.
[22] Moubrary J. RCM II: reliability centered maintenance. Industrial Press Inc; 2001.
[23] Smith, D.K. (2011). Variable failure rates and probability plotting. reliability, maintainability and risk (8th Edition), Butterworth-Heinemann, 2011, 71–83, ISBN 9780080969022.
[24] O'Connor P, Kleyner A. Practical reliability engineering. 5th Edition. Chichester, UK: John Wiley & Sons; 2012.
[25] Thanh Thach T, Briš R. An additive Chen-Weibull distribution and its applications in reliability modeling. Qual Reliab Eng Int 2020:1–22. https://doi.org/10.1002/qre.2740.
[26] Tarvirdizade B, Ahmadpour M. A new extension of chen distribution with applications to lifetime data. Commun. Math. Stat. 2021;9:23–38. https://doi.org/10.1007/s40304-019-00185-4.
[27] Xie M, Tang Y, Goh TN. A modified Weibull extension with bathtub-shaped failure rate function. Reliab Eng Syst. Saf. 2002;76:279–85. https://doi.org/10.1016/S0951-8320(02)00022-4.
[28] Abba B, Wang H, Bakouch HS. A reliability and survival model for one and two failure modes system with applications to complete and censored datasets. Reliab Eng Syst. Saf. 2022;223:108460. https://doi.org/10.1016/j.ress.2022.108460.
[29] Akaike Hirotugu. «A new look at the statistical model identification». IEEE Trans Automat Contr 1974;19(6):716–23. https://doi.org/10.1109/TAC.1974.1100705. MR 0423716.
[30] Schwarz G. Estimating the dimension of a model. Ann Stat 1978;6:461–4.
[31] Hastie T, Tibshirani R, Friedman JH, Friedman JH. The elements of statistical learning: data mining, inference, and prediction, 2. New York: springer; 2009. p. 1–758.
[32] Aalen OO. Nonparametric inference for a family of counting processes. Ann Statist 1978;6:701–26.
[33] Kim HJ, Fay MP, Feuer EJ, Midthune DN. Permutation tests for joinpoint regression with applications to cancer rates. Stat Med 2000;19:335–51.