Effect of test-caused degradation on the unavailability of standby safety components

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ABSTRACT

This paper proposes a safety-critical standby component unavailability model that contains aging effects caused by the elapsed time from installation, component degradation due to surveillance tests, and imperfect maintenance actions. An application of the model to a Motor-Operated Valve and a Motor-Driven Pump involved in the HPIS of a VVER/1000-V446 nuclear power plant is demonstrated and compared with other existing models at component and system levels. In addition, the effects of different unavailability models are reflected in the NPP’s risk criterion, i.e., core damage frequency, over five maintenance periods. The results show that, compared with other models that do not simultaneously consider the full effects of degradation and maintenance impacts, the proposed model realistically evaluates the unavailabilities of the safety-related components and the involved systems as a plant age function. Therefore, it can effectively reflect the age-dependent CDF impact of a given testing and maintenance policy in a specified time horizon.

1. Introduction

Surveillance testing is a requirement outlined in the technical specifications (TS) for nuclear power plants (NPPs). These tests are conducted on safety-significant components, typically monthly, and occasionally even more frequently. The purpose of these tests is to ensure that the standby safety systems will start and fulfill their intended functions in the event of any abnormality at the plant. When considering risk reduction, one positive aspect of testing is the ability to detect any previously unrevealed faults in the components. This is particularly relevant when performing the test following the last surveillance test inspection (STI). In addition to these positive aspects, surveillance tests can also have undesirable side effects and lead to several risk contributions. These risks include the possibility of initiating plant transients during testing, \( R_{\text{rip}} \), progressive wear-out of equipment caused by the accumulation of test-induced degradation, \( R_{\text{wear}} \), misconfigurations or restoration errors, \( R_{\text{data}} \), downtime required for conducting the test, \( R_{\text{down}} \), and unnecessary cumbersome and radiation exposure for plant personnel. The accumulation of these aggregative effects will result in increased unavailability of the component, consequently affecting the unavailability of the associated safety system and its functions. As a result, the plant’s capability to prevent or mitigate an accident will be diminished [1–3].

To identify the primary risk contributors in an NPP, the practice of utilizing Probabilistic Safety Assessment (PSA) modeling has been ongoing. This approach allows for the consideration and quantification of risk criteria, such as Core Damage Frequency (CDF). PSA also serves as a crucial tool in quantitatively evaluating the risk impact resulting from the plant’s TSs. These TSs establish the operational limits and conditions for both NPP and aging equipment throughout its operational life [1,4,5]. The current PSA models and data do not explicitly incorporate the effects of TS activities and equipment aging. However, it is important to recognize that these factors can have a substantial impact on the conclusions drawn from the PSA. The omission of these considerations introduces a significant level of uncertainty, particularly when NPPs are operated over extended periods. Therefore, it is crucial to address and incorporate the influence of TS activities and equipment aging to enhance the accuracy and reliability of PSA assessments for long-term NPP operation [4]. To tackle the aforementioned issues, numerous pioneering studies have focused on developing reliability and unavailability models for components. These models explicitly incorporate considerations of TS requirements and the aging of components.

A methodology was proposed to analyze the unavailability of a safety-related component that undergoes periodic testing and
maintenance under specific policies. This approach involves a discrete renewal process that incorporates the effects of surveillance and maintenance factors [6]. Time-dependent unavailability models have also been developed for periodically tested components that follow common maintenance policies and are characterized by failure probability distributions [7,8]. Furthermore, a methodology has been devised for modeling time-dependent component unavailability, specifically considering repair activities, by extending the classic renewal equation [9,10]. In addition, recursive and time-dependent unavailability models have been developed, which are explicit expressions that account for constant standby failure rates, excluding aging and test-induced degradation effects [11–16]. In the exploration of periodically tested component unavailability models, researchers have conducted studies that quantify the adverse effects of tests on risk [2,3]. The models developed in these studies consider the concept of risk-effectiveness and employ the most comprehensive time-dependent component unavailability model. Some of the simplified unavailability models in Refs. [2,3] were developed based on Linear and Weibull aging models and proposed for sequential and staggered tested components [17]. An age-dependent unavailability standby equipment model is developed within [18] and includes aging-relevant information and enhancement strategies of availability, i.e., OMIM and SSTIM. A model for component unavailability proposed in Ref. [3], is developed by considering the degradation caused by unplanned demands, without taking into account the effectiveness of maintenance activities [19]. The presented reliability, availability, and maintainability (RAM) models of safety-related components explicitly incorporate the aging effects, maintenance effectiveness, operational conditions, test efficiency, and imperfect maintenance models when determining the component standby failure rates. However, the models do not explicitly consider the degradation effects caused by testing, specifically related to demand and standby stress, in the reliability model of safety-significant components [4,20,21]. A RAM model of a safety-significant component has been developed with a focus on the demand-caused failure probability contribution. This model explicitly involves the effects of demand stresses, the effectiveness of maintenance activities, including Proportional Age Setback (PAS) and Proportional Age Reduction (PAR) models, and the efficiency of tests [22]. Other time-dependent unavailability models for safety components consider the effects of aging, and testing, as well as the effectiveness of corrective, preventive, and overhaul maintenance. However, these models do not explicitly account for the degradation effects caused by testing [1,23]. Previous researches have indicated that predictive unavailability models should generally incorporate factors such as the number of tests, aging, the effectiveness of maintenance activities, and test efficiency. However, these studies have given limited attention to the test-caused component degradation effects associated with standby failures which are partially compensated by implementing maintenance activities to reduce the accumulated degradation. It is clear that as the level of stress increases, the region of chance failure in the bathtub curve decreases, and premature wear-out occurs [24]. To establish a comprehensive component unavailability model, all aspects of the test, regardless of significance, should be considered [2,3,18]. Therefore, as a part of the decision-making process related to the improvement maintenance policies of standby components, e.g., reliability-centered maintenance (RCM) programs, the test-caused degradation effect has been recognized as a matter of concern and must be evaluated during an NPP lifetime [2,3].

The primary objective of this paper is to investigate the impact of planned inspections on the unreliability contribution specifically associated with the standby time-related failure rate of safety-significant components. To address this, an innovative age-dependent model for estimating the unavailability of standby components is proposed. This model takes an integrated approach by explicitly considering all information related to component deterioration. It incorporates factors such as aging effects, the number of tests conducted and their associated degradations on standby time-related failure rate, the elapsed time since installation, and the effectiveness of maintenance activities. The proposed component’s unavailability model along with other alternative models are applied in the level 1 PSA model of a VVER/1000-V446 Pressurized Water Reactor (PWR) and compared. These component unavailability models are incorporated into the Fault Tree (FT) model of a High-Pressure Injection System (HPIS) which includes the Motor-Operated Valve (MOV) and Motor-Driven Pump (MDP) components and evaluate the unavailability of the HPIS. Furthermore, the unavailability of the HPIS is utilized to quantify the risk measure of the plant, specifically the CDF in the event of a steam generator tube rupture (SGTR) through the Event Tree (ET) model.

The rest of this paper is structured as follows: the proposed model formulation is presented in section 2. Section 3 describes a case study, and the component unavailability model application is evaluated and
compared with the other models. In section 4, results are presented by using an available PSA model of VVER/1000-V446 PWR for different models. Lastly, section 5 presents some conclusions.

2. Unavailability model based on the concept of stress on the component

The aging effects and test-caused degradations are induced by two kinds of stresses, i.e., standby and demand stresses, respectively. The standby or time-related stress affects the component in the standby state. While the demand or cycle-related stress acts only when the component is asked to function or is operating. Generally, for the standby components that are periodically tested to detect hidden failures, the combination of both stresses causes the component to degrade, and ultimately fail [2,3].

Based on the component degradation mechanisms caused by testing and aging, a well-organized foundation in modeling component unavailability contributions, i.e., demand failure probability and standby time-related failure rate, was proposed by Kim et al. [2,3]. This more realistic unavailability model of a safety component accounts for aging and the adverse effects of testing is as follows [2,3]:

\[
q(t) = \rho(n) + \int_{at}^{t+\alpha t} \lambda(n, t) \, dt \quad \text{for } t \in [0, T]
\]  

(1)

Due to insufficient data availability, Kim et al. proposed a simplification of the earlier two basic degradation parameters, \(\rho(n)\), \(\lambda(n, t)\), including linearized their models. The component demand failure probability, \(\rho(n)\), is only affected by frequent testing, as a progressive wear-out, and modeled as a function of the number of performed tests, \(n\), i.e.,

\[
\rho(n) = \rho_0 + \rho_1 n
\]  

(2)

The progressive wear-out on the standby-related failure rate is due to the number of tests, \(n\), as well as the chronological time, \(t\), and modeled as follows

\[
\lambda(n, t) = \lambda_0 + \lambda_1 n + \alpha t
\]  

(3)

Where,

- \(n\) = the number of tests performed on the equipment at the chronological time.
- \(t\) = time elapsed since the last test
- \(\rho_0\) = residual demand failure probability
- \(T\) = test interval.
- \(p_1\) = test degradation factor associated with demand failures
- \(p_2\) = test degradation factor for standby time-related failures
- \(\lambda_0\) = residual standby time-related failure rate
- \(\alpha\) = aging factor associated with pure aging [2,3,7,22].

The estimation of the probability of failure on demand (PFD) for a safety component can be achieved by considering both demand and standby-related failure modes using Eqs. (1)-(3). Eqs. (2) and (3) demonstrate that \(\rho(n)\) and \(\lambda(n, t)\) are influenced by test stress, specifically the number of tests, while \(\lambda(n, t)\) is affected by standby stress, specifically elapsed time. This assignment is based on the NRC’s classification report, which indicates that different equipment elements may be differently impacted by each type of stress. Therefore, the assignment of standby stress only to \(\lambda(n, t)\) suggests that standby stress deteriorates certain elements, such as those composing the equipment, whereas test stress may affect all the equipment elements [18,25,26].

2.1. Demand-caused failure probability model addressing demand-induced stress and maintenance effectiveness: \(\rho(n, m, \varepsilon_0)\)

Based on Eq. (2), the demand failure probability for a standby component that is ready to perform a safety function on demand depends only on the number of demands. These demands involve the planned surveillance and functional tests existing in NPP’s TS, the unplanned tests after corrective maintenance, and operational demands. The most significant contribution of these demands is related to surveillance tests on the safety component [2,22].

By assuming constant surveillance test and maintenance intervals given by \(T\) and \(M\) as a regular basis for performing test and PM activities, Fig. 1 illustrates the proportional time relation between them.

The time-dependent failure probability on demand-caused failures after performing \(m\) PAS imperfect maintenance activities and \(n\) specified tests, based on the proposed model in Ref. [22], could be formulated as:

\[
\rho_{\text{PAS}}(n, m, \varepsilon_0) = \rho_0 + \rho_1 (1 - \varepsilon_0)^m \frac{T_{PM}}{T} \left(1 - \rho_1 (1 - \varepsilon_0) \frac{m}{T} \right) + ... + \rho_1 (1 - \varepsilon_0)^m \frac{T_{PM} - T_{PM-1}}{T} + \rho_1 (1 - \varepsilon_0)^m \frac{T_{PM} - T_{PM-1}}{T} + ...
\]  

(4)

Where \(n = \lceil \frac{T}{T} \rceil\) just includes the number of surveillance tests performed on the safety component up to time \(T\) and \(\lceil x \rceil\) is the floor function [22]. The primary concept underlying the PAS model is that each maintenance activity is presumed to proportionally reduce the overall degradation of the component just before it undergoes maintenance. This reduction factor, denoted as \(\varepsilon_0\), represents the maintenance effectiveness and can vary between 0 and 1 [1,4,21,22]. Then, by using the geometric series equivalent relation Eq. (4) has simplified as follows [22].

\[
\rho(n, m, \varepsilon_0) = \rho_0 + \rho_1 (1 - \varepsilon_0)^m \frac{M}{T} \left(1 - \varepsilon_0 \frac{m}{T} \right)^n \left(1 - (1 - \varepsilon_0)^n \right)
\]  

(5)

2.2. Standby time-related failure rate modeling

2.2.1. Addressing demand and standby stresses: \(\lambda(n, t)\)

There might be two fundamental causes of equipment degradation. First, waiting time could deteriorate the component condition. The condition of components installed many years ago would differ from those recently installed. “Standby stress”, i.e., aging, leads to this difference and accumulates over time. Second, numerous tests or operations may degrade components. The component could be worn down and deteriorate its condition at each test. The condition of the component tested or operated many times would be different from the component only tested one time. “Test stress” causes this difference which is accumulated by performing the tests. For a more realistic standby time-related failure modeling for the standby component, both stresses, including standby and test stress, should be considered together [1,3,16,27]. Additionally, the effectiveness of maintenance activities, aimed at mitigating the adverse effects of aging and testing, should be taken into account to improve component reliability [3,4,18].

In general, to evaluate the failure rate or unavailability involved in test-caused degradations after a long period, both effects should be taken into account. Because aging and degradation effects caused by elapsed time and the number of tests, respectively, are not negligible. In such a case, different models of component reliability, such as linear, Weibull, Exponential, etc., have been proposed in the literature that address the component aging effects [1,3,28]. The most comprehensive component standby time-related failure rate model can next be formulated as a function of the elapsed time, \(t\), and the number of tests, \(n\), based on the proposed model in [3]:

\[
\lambda(f(t), w(t)) = \lambda_0 + \lambda_1 f(t)^\beta_1 + \alpha w(t)^\beta_2
\]  

(6)

Due to the test and aging impact parameters, i.e., \(\beta_1\) and \(\beta_2\), cannot be easily estimated based on the typical available data, and thus, they are set as 1 [2,3,22]. Therefore, this paper assumes that the failure rate has a linear behavior with the age and degradation caused by the elapsed time and the number of tests on the component and the simplest
age-dependent reliability model will be constituted. Where in Eq. (6), $f_2(t)$ is a degradation function caused by demand stresses and depends on the number of all demands. By assuming that for all types of demands, the degradation factor is the same and equal to, the degradation function can be formulated as follows:

$$f_2(t) = p_m(n(t))$$

and $w(t)$ is the component age and the evolution of the component age is given by [4, 28]

$$w(t) = w_n + (t - t_m)$$

Where $w_n$ is the age of the component immediately after performing $m^\text{th}$ maintenance activity at the time of $t_m$, and $t$ is the chronological time elapsed since the component’s installation. So, the standby time-related failure rate model can be expressed as

$$\lambda(n, t) = \lambda_0 + \lambda_0 p_2 [\frac{t}{T}] + \alpha (t)$$

(7)

2.2.2. Addressing maintenance effectiveness: $\lambda(n, m, t, \epsilon_s)$

As mentioned earlier, the PAS maintenance model incorporates a factor called maintenance effectiveness ($\epsilon_s$) to proportionally reduce the component degradation condition immediately prior to the maintenance activity. This factor is predetermined for each PM activity and falls within the interval of $[0, 1]$. Therefore, the maintenance activities gradually reduce the incline of the age-dependent failure rate $\lambda(n, t)$ [4, 23, 27].

The effect of the PM modeling should be shown at Eq. (9) as a base equation, then up till the first PM, i.e., $t \in [0, T_{PM_1})$, the considered component failure rate will be equal to:

$$\lambda_{PM_1}(n, t) = \lambda_0 + \lambda_0 p_2 [\frac{t}{T}] + \alpha (t)$$

(10)

After performing the first PM, i.e., $t \in [T_{PM_1}, T_{PM_2})$, it will be

$$\lambda_{PM_1}(n, t, \epsilon_s) = \lambda_0 + \left(\alpha (T_{PM_1}) + \lambda_0 p_2 \left[\frac{T_{PM_1}}{T}\right]\right) (1 - \epsilon_s) + \alpha (t - T_{PM_1})$$

(11)

After performing the second PM, i.e., $t \in [T_{PM_2}, T_{PM_3})$, it will be

$$\lambda_{PM_1}(n, t, \epsilon_s) = \lambda_0 + \left(\alpha (T_{PM_2} - T_{PM_1}) + \lambda_0 p_2 \left[\frac{T_{PM_2} - T_{PM_1}}{T}\right]\right) (1 - \epsilon_s)$$

(12)

By assuming a constant maintenance interval given by $M$ to perform PM activities, Eq. (12) can be simplified as follows:

$$\lambda_{PM_1}(n, t, \epsilon_s) = \lambda_0 + \left(\alpha (M) + \lambda_0 p_2 \left[\frac{M}{T}\right]\right) (1 - \epsilon_s)^j + \alpha (t - T_{PM_1})$$

$$+ \lambda_0 p_2 \left[\frac{t - T_{PM_1}}{T}\right] = \lambda_0$$

$$+ \sum_{j=0}^{n-1} \left(\alpha (M) + \lambda_0 p_2 \left[\frac{M}{T}\right]\right) (1 - \epsilon_s)^{j+1}$$

$$+ \alpha (t - T_{PM_1}) + \lambda_0 p_2 \left[\frac{t - T_{PM_1}}{T}\right]$$

$$+ \alpha (t - T_{PM_1}) + \lambda_0 p_2 \left[\frac{t - T_{PM_1}}{T}\right]$$

(13)

The summation term in Eq. (14), corresponds to a geometric series with the first term and the common ratio being 1 and $(1 - \epsilon_s)$, respectively. Then Eq. (14) can be simplified as follows

$$\lambda_{PM_1}(n, t, \epsilon_s) = \lambda_0 + \left(\alpha (M) + \lambda_0 p_2 \left[\frac{M}{T}\right]\right) (1 - \epsilon_s)^j + \alpha (t - T_{PM_1})$$

$$+ \lambda_0 p_2 \left[\frac{t - T_{PM_1}}{T}\right]$$

(15)

2.3. Time-dependent unavailability of a standby component

Based on Eq. (1), the time-dependent failure probability of a standby component is modeled as a combination of the demand-caused failure probability and integration of standby time-related failure over time. Inserting Eqs. (5) and (15) into Eq. (1), then yields Eq. (16) for the most comprehensive time-dependent component unavailability model that takes into account aging effects, test-caused degradation, and PM activities:

![Fig. 1. Schematic description of tests and maintenance intervals.](image-url)
\[ q(n, t, m, \varepsilon) = p_0 + \rho_0 p_n \frac{M}{T} \left(\frac{1 - \varepsilon_0}{\varepsilon_0}\right) \left(\frac{1}{1 - (1 - \varepsilon_0)^n}\right) + \rho_0 p_T \left(\frac{1}{T}\right) + \lambda_0 t \]
\[ + \lambda_0 p_2 \frac{M}{T} \left(\frac{1 - \varepsilon_1}{\varepsilon_1}\right) \left(\frac{1}{1 - (1 - \varepsilon_1)^n}\right) t \]
\[ + \alpha M \frac{(1 - \varepsilon_1)}{\varepsilon_1} \left(\frac{1}{1 - (1 - \varepsilon_1)^n}\right) t \]
\[ + \alpha \left(\frac{t^2 + 2t T}{2} - m M t\right) \]
\[ (16) \]

Where the number of tests, i.e., \( n \), is equal to the floor function \( \lfloor \frac{T}{t} \rfloor \).

For convenience, the proposed model is named Case 3. To compare the component unavailability of different models developed in the context of incorporating degradation and aging into modeling, two component unavailability models are introduced. These models are without consideration of maintenance effectiveness \([2,3,19]\) and test-caused degradation \([1,4,20,22,23,27]\) and for simplicity named Case 2 and Case 1, respectively.

Case 1. Takes into account the test-caused degradation and aging effects on demand caused failure probability and standby time-related failure, but the effectiveness of maintenance activities is not considered.

Case 2. Considers the effects of maintenance activities on both unavailability contributions, i.e., the demand-caused failure and the standby time-related failure. Still, in this case, the test degradation effects are only considered on the earliest contribution, i.e., the demand-caused failure, and the standby time-related failure rate has been ignored. These cases, their characteristics, and their mathematical models are shown in Table 1.

### 2.4. Averaged unavailability of a standby component

The average unavailability in the time period of a surveillance test interval, the time period between \( nT \) and \( (n + 1)T \) for the \( n \)th test interval can be evaluated by Eq. (17), where \( n = 1, 2, 3, \ldots, N \) and \( N = \frac{M}{T} \).

\[ \bar{q}(n, m, \varepsilon) = \frac{1}{N} \int_{nT}^{(n+1)T} q(n, t, m, \varepsilon) dt \]
\[ (17) \]

By substituting Eq. (16) into Eq. (17), the average unavailability of the standby component between two consecutive surveillance tests \( n \) and \( n + 1 \) is given by:

Finally, as an effective measure during a working cycle, i.e., between two consecutive refueling cycles, the average component unavailability can be estimated as follows:

\[ \overline{q}(m, \varepsilon) = \frac{1}{N} \sum_{n=0}^{N-1} \bar{q}(n, m, \varepsilon) \]
\[ (19) \]

Where \( N \) is the total performed tests in each PM interval.

Consequently, this proposed model can be applied to a level 1 PSA model and allows for the assessment of the CDF results from the impact of aging, test-caused degradation, and maintenance effectiveness on the standby component.

### 3. Application to a case study

#### 3.1. Problem description

All three component unavailability models, i.e., Cases 1, 2, and 3, are generic and can be used for any kind of component. To ensure simplicity in the discussion of results, the application of these models is limited to quantifying basic events associated with the main components of the HPISs within the Emergency Core Cooling System (ECCS) of the VVER/1000-V446 nuclear reactor. Specifically, this application is focused on the five refueling cycles. In accordance with the level 1 standard PSA of the VVER/1000-V446 plant, the unavailability of the HPIS is accounted for in four distinct failure modes, including components’ unavailability, common cause failure, and human and software errors \([30]\). The level 1 standard PSA of the VVER/1000-V446 plant was modeled using the SAPHIRE software tool \([31]\). The unavailability of the HPIS is represented by an FT model, which considers the unavailability of the MOV and MDP resulting from test activities and random failures through the developed Python script codes. Furthermore, it is crucial to assess the adverse safety impact of excessive surveillance testing from a risk perspective, as it provides valuable insights for decision-making. To address this concern, the FT model of the HPIS is linked to the event tree.

### Table 1

Comparison of the component unavailability models.

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Component unavailability contributions</th>
<th>Standby stress</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Demand stress</td>
<td></td>
</tr>
<tr>
<td></td>
<td>( p(n) )</td>
<td>( \lambda_0 + \rho_0 p_T \left(\frac{1}{T}\right) + \frac{\alpha M T}{T} ) ( t )</td>
</tr>
<tr>
<td>Case 1 ([2,3,19])</td>
<td>( p_1, p_2a )</td>
<td>( \rho_0 + \rho_0 p_T \left(\frac{1}{T}\right) + \frac{\alpha M T}{T} ) ( t )</td>
</tr>
<tr>
<td>Case 2 ([1,4,20,22,23,27])</td>
<td>( p_1, a, \varepsilon_0 )</td>
<td>( \rho_0 + \rho_0 p_T \left(\frac{1}{T}\right) + \frac{\alpha M T}{T} ) ( t )</td>
</tr>
<tr>
<td>Case 3</td>
<td>( p_1, p_2, a, \varepsilon_0 )</td>
<td>( \rho_0 + \rho_0 p_T \left(\frac{1}{T}\right) + \frac{\alpha M T}{T} ) ( t )</td>
</tr>
</tbody>
</table>
model, which is also constructed using the SAPHIRE tool. This allows the adverse effect to be reflected in the level 1 plant risk criterion, namely CDF.

### 3.2. System description

The ECCS of a 4-loop VVER/1000-V446 nuclear reactor comprises four independent trains and performs multiple functions. The structural and physical configurations of all trains are similar and all safety function requirements can be provided by each train in all situations \[25, 26\]. Each train has an HPIS as an active part that is on stand-by during normal operation. Under the emergency condition of leakage from the primary into the secondary circuit, e.g., in an SGTR accident, when the pressure in the primary circuit becomes less than 7.8 MPa, the HPIS performs an "F function" to maintain coolant inventory in the core. In this function, the HPIS consists of one MDP and four MOVs that periodically undergo surveillance tests and maintenance activities. In the F function, valves TH15(25,35,45) S011 and S012 on the recirculation line close and then valves TH15(25,35,45) S003 and S007 on the two injection paths open and pump TH15(25,35,45) D001 supply boric acid solution from 2х197,5 m³ tanks TH10(20,30,40) B001 and B002 in each train \[29, 30\].

Table 2 presents the failure rate values and the test and maintenance intervals for a single train of the HPIS, specifically the MDP and MOV. These values have been derived from the available PSA data and the current TS of the VVER/1000-V446 nuclear reactor. Table 3 presents the constant parameter values associated with the proposed model for a single train of the HPIS. The value of \(\rho_0\) is obtained from Refs. \[27, 31, 32\], while the values of \(\alpha\) are obtained from the TIRGALEX database, which is a generic database developed by the NRC \[33\]. However, the existing component failure database typically does not provide specific values for \(p_1\) and \(p_2\). Consequently, as a conservative assumption, their maximum values are estimated using the parameter values in Tables 2 and 3, along with the derived formulas available in NUREG/CR-5775 \[3\]. Regarding the estimation of maintenance effectiveness parameters, denoted as \(\lambda_1, \lambda_2\), this paper adopts the methodology proposed in Ref. \[31\], where both parameters are set to 0.6. It is important to note that the estimation of these parameters in the modeling of component behavior is a council task and their usage may introduce a significant level of uncertainty to the results. However, they can still provide reasonable measures, as mentioned in Refs. \[18, 20, 26, 31\].

The failure logic of each HPIS is considered by the FT model that is taken from the available Level 1 standard PSA of the VVER/1000-V446 nuclear reactor. The applied FT model is developed at a component level and adapted by integrating the introduced models in the previous section. Therefore, the FT of each HPIS uses the introduced models of component unavailability for the determination of the probabilities of the basic events representing MDP and MOV failures which are shown in Table 2.

### 3.3. Risk assessing

As mentioned earlier, the level 1 standard PSA of the VVER/1000-V446 plant in full-power operation is adopted to evaluate the risk metric of CDF. This risk metric related to the accident sequences resulting from the SGTR initiating event is assessed by its ET model existing in the available PSA \[30\]. Hence, by applying this approach, the CDF caused by the SGTR initiating event of the VVER/1000-V446 nuclear reactor can be obtained as a function of the impact of aging, test-caused degradation, and maintenance policies.

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**Table 2**

<table>
<thead>
<tr>
<th>No.</th>
<th>Component Code</th>
<th>Component Type</th>
<th>Failure Rate (\lambda_0) (h(^{-1}))</th>
<th>(T) (h)</th>
<th>(M) (h)</th>
<th>Basic Event</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>TH15D001PMS</td>
<td>MDP</td>
<td>2.35E-6</td>
<td>672</td>
<td>8064</td>
<td>Fail to start</td>
</tr>
<tr>
<td>2</td>
<td>TH15S003VMO</td>
<td>MOV</td>
<td>1.78E-6</td>
<td></td>
<td></td>
<td>Fail to open</td>
</tr>
<tr>
<td>3</td>
<td>TH15S007VMO</td>
<td>MOV</td>
<td>1.78E-6</td>
<td></td>
<td></td>
<td>Fail to open</td>
</tr>
<tr>
<td>4</td>
<td>TH15S011VMO</td>
<td>MOV</td>
<td>1.78E-6</td>
<td></td>
<td></td>
<td>Fail to close</td>
</tr>
<tr>
<td>5</td>
<td>TH15S012VMO</td>
<td>MOV</td>
<td>1.78E-6</td>
<td></td>
<td></td>
<td>Fail to close</td>
</tr>
</tbody>
</table>

**Table 3**

<table>
<thead>
<tr>
<th>Component</th>
<th>(\rho_0) (h(^{-1}))</th>
<th>(\alpha) (h(^{-2}))</th>
<th>(p_1)</th>
<th>(p_2)</th>
<th>(\epsilon_D)</th>
<th>(\epsilon_s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MDP</td>
<td>0.53E-3</td>
<td>0.22E-10</td>
<td>0.0107</td>
<td>0.004</td>
<td>0.6</td>
<td>0.6</td>
</tr>
<tr>
<td>MOV</td>
<td>6.42E-3</td>
<td>3.42E-10</td>
<td>0.0138</td>
<td>0.138</td>
<td>0.6</td>
<td>0.6</td>
</tr>
</tbody>
</table>

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**Fig. 2.** Demand-caused failure probability of components.
4. Results and discussion

This section presents the results of implementing the proposed model and other existing models, i.e., Case 3, Case 2, and Case 1, respectively, on MDP and MOVs of HPIS. These results include the time-dependent demand-caused failure probability, the time-dependent standby-related failure, the averaged component unavailability during two consecutive surveillance tests and PM activities. Then, the HPIS unavailability and the CDF values are evaluated and compared by the various component aging models.

Fig. 2 (a)-(b) shows that for both components, i.e., MDP and MOV, the demand-caused failure probability is ever-increasing with chronological time for Case 1 and has an asymptotic behavior for Cases 2 and 3. For both components in all cases, the evolution of demand failure probability only results from the test degradation effects associated with demands and aging has no effect. The differences in behavior of these cases are due to the fact that in Case 1, no maintenance activities are implemented, while in Cases 2 and 3, maintenance activities are performed every refueling period of the plant. In this figure, it can be seen that up till to the first maintenance activity, all cases have a similar monotonically increasing behavior. Also, Cases 2 and 3 always have identical behavior because their models are the same. Due to the used

maintenance model, i.e., the PAS model, the component demand-caused failure probability has the asymptotic behavior over time. Therefore, it can be interpreted that the constant maintenance activities keep the demand-caused degradation of the component at a residual or constant level in the long term.

Fig. 3 (a)-(b) shows both components’ standby time-related failure rate behaviors over chronological time. Due to no maintenance activities being done for each of the components, the standby time-related failure rate on Case 1 is ever-increasing over time. Whereas, in the other Cases, i.e., Case 2 and Case 3, due to the specified maintenance activities, standby time-related failure rates have monotonically increased behaviors and ultimately reach the asymptotic manners. Regarding the standby time-related failure models, up until the first preventive maintenance activity, Cases 1 and 3 have similar behaviors. But in Case 2, the component standby time-related failure rate functions evolve over time without any effect of the test degradations being applied and have linear behaviors induced by the aging model. Therefore, for both components, the standby time-related failure is underestimated by using Case 2. So, as shown in Fig. 3, it is clear that the aging and test-caused degradation impacts are closely dependent and synergize with each other. Among all cases, Case 3 is the most complete and able to predict the most realistic standby time-related failure rates. By comparing Case 2 and Case 3, i.e.,

Fig. 3. Standby time-related failure rate of components.

Fig. 4. Average unavailability over the consecutive tests.
without and with test-caused degradation effect on standby time-related failure rates and while keeping the same maintenance activities, for example, it is observed an increase of 6.23 % and 40 % in the standby time-related failure rates of the MDP and MOV at the end of the fifth working cycle, respectively.

For a 336-day maintenance activity and a 28-day testing scheme, Fig. 4 (a)-(b) shows the results achieved for the averaged unavailability evolution on the MDP and MOV in the time period of the consecutive surveillance tests for the different Cases. The highest values of the averaged unavailabilities are reached by adopting Case 1, i.e., without implementing continuous maintenance activities. Observing the behavior of the averaged unavailabilities on Case 1 for both components, it is possible to see their evolutions from the base values of 0.0018 and 0.0070 to the maximum values of 0.0027 and 0.0209 for the MDP and MOV at the fifth working cycle, respectively. In Case 2, which is not included the test caused degradation contribution on the standby time-related failure rate of the components, the averaged unavailability values are equal to Case 1 and also Case 3 is very performing the first test on the first maintenance interval. After that, the Case2 averaged unavailability behavior is distinguished from the other Cases because, in this case, the test-caused degradation effect on standby time-related failure rate was neglected. As illustrated in Fig. 4, Case 1 and Case 3 are matched together until the implementation of the first maintenance activity. Then due to performing the maintenance activities, Case 3 has a monotonically increasing behavior which is converted to the asymptotic behavior ultimately. By comparing Case 3 and Case 2, because of considering the test-caused degradation contribution on standby time-related failure rate in Case 3, the averaged component unavailability is greater than Case 2 in all working cycles. For example, in Case 3 and Case 2, the maximum average unavailability values of MDP and MOV are 0.00211, 0.00202, 0.01142, and 0.00995, respectively, at the end of the fifth working cycle. It is observed that an increase of 4.26 % and 12.87 % in the averaged unavailability values of MDP and MOV, respectively. Therefore, neglecting the test-caused degradation effect on standby time-related failure rate could lead to a reasonable error in estimating the averaged unavailability at the component level.

Fig. 5 (a)-(b) shows the average unavailability evolution on the MDP and MOV over a five-working cycle period for all cases. For both components, as expected, the highest values of unavailability are related to Case 1, i.e., without implementing the maintenance activities during the refueling periods. From both figures, it can be seen that before performing the first maintenance activity, the average unavailability of Case 1 is as same as Case 3, whereas this value is underestimated by Case 2 because the presence of test-degradation effects is neglected in this case. By implementing the maintenance activities with constant features, i.e., maintenance interval and effectiveness, the asymptotic behaviors are reached for Cases 2 and 3. This is a natural consequence, the component’s state can be further improved by performing regular maintenance activities. As shown in Fig. 5, the asymptotic unavailability values for the MDP tend to be 0.0019 and 0.0020 and for the MOV tend to be 0.009 and 0.01 in Case 2 and Case 3, respectively. At the end of the fifth cycle, for example, the average unavailability values provided by Cases 2 and 3 have 3.4 % and 10.37 % differences for the MDP and MOV, respectively. In addition, the slope of the component unavailability evolution increases when the test-caused degradation effects of standby time-related failure rate, i.e., Case3, are considered and later reached to the asymptotic behavior, compared with Case2, which is eliminated this contribution.

To assess the system unavailability and the CDF as a function of the plant age which explicitly addresses the impacts of testing and maintenance, the component unavailability models, i.e., Cases 1, 2, 3, are used in the level 1 standard PSA model of the VVER1000/V446. Where the quantified values related to the component unavailabilities are obtained from the usual, existing in the PSA, to those which explicitly incorporate aging, i.e., Cases 1, 2, 3, as have been evaluated in the past.

Fig. 6 (a) Shows the HPIS unavailability evolution over different working cycles for all three cases. As expected, without performing the maintenance activities, i.e., in Case 1, the HPIS unavailability values increase over the working cycles. At the end of the first working cycle, it is demonstrated that the HPIS unavailability values of Case1 and Case 3 are equal, while Case 2 represents a smaller value. This confirms that Case 2 is incomplete due to neglecting the test-caused degradation contribution on the standby time-related failure rate of the MDP and MOV. It can be observed in Fig. 6 (a)–(b) that the predictive unavailability assessment of Case 3 is larger than Case 2 at all of the working cycles, and this difference would be increased over time, Fig. 6(b). For example, comparing the unavailability value predicted by Case 2 with Case 3, it is observed that an increase of just 0.17 % at the end of the fifth working cycle. Also, the asymptotic behavior of unavailability of Case 3 would happen later than Case 2, because of the accumulation of both the test-caused degradation and aging effects related to the HPIS components. Fig. 6 shows that the increase in HPIS unavailability is more significant in the primary cycles and could be controlled by performing a suitable maintenance program. Therefore, it is possible to conclude that the evolution of the accumulated effects of aging and the excessively test-caused degradation of the HPIS will practically lead to an asymptotic behavior by taking into account adopting an appropriate maintenance strategy.

Fig. 7 (a) shows the CDF values resulting from the SGTR initiating event for the five working cycles. It is clear that the maintenance activity

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**Fig. 5.** Average unavailability over the consecutive preventive maintenance.
contributes to a significant decrease in the CDF values, and for Case 1, i.e., without maintenance activities, can be observed that considerable CDF increments. It indicates that the absence of maintenance activities may substantially affect the risk criterion of CDF. It is observable in Fig. 7 (a) that Cases 1 and 3 have the same value and are larger compared to Case 2 at the end of the first working cycle. Fig. 7 (b) indicates that the evolution of the CDF increases and its asymptotic behavior is reached later when the test-caused degradation effects are considered at the component level, i.e., Case 3, in comparison with Case 2. Comparing the CDFs result from these two cases at the end of five working cycles, for example, would lead to an increase of 0.22% for Case 3, which confirms the global contribution of tests to the growth of the CDF. These results indicate that the accumulation of the planned tests policy-caused degradation and the aging effects may lead to a global increase in the risk criterion of CDF. By performing an effective maintenance strategy, a constant level of CDF would possibly be kept in the long term.

5. Conclusion

This study proposes a novel approach for modeling the unavailability of critical components in the safety systems. The model takes into account the cumulative test-caused degradation effects, aging, and maintenance effectiveness, all of which contribute to the total failure rate of safety significant components. The model is applied to evaluate the unavailability of critical components, i.e., MDP and MOVs, in the HPIS of the VVER-1000/V446 NPP’s ECCS and is compared to existing models. The results at the component level demonstrate that the proposed model, which comprehensively accounts for significant degradation, aging, and maintenance effects, provides more accurate and realistic calculations of unavailability compared to incomplete models that either underestimate or overestimate it. By applying all three models to the existing level 1 PSA model of the VVER-1000/V446 NPP, the enhanced unavailability of the HPIS and CDF related to SGTR event, which explicitly incorporate factors such as aging, test-caused degradation, and maintenance effectiveness, exhibit an increase when compared to their values in the standard PSA model. Further, employing the comprehensive proposed model yields more realistic results and can be effectively utilized for the planning and management of test and maintenance programs. Moreover, the proposed model, which incorporates all aspects of test-caused degradation effects as well as other significant factors proposed in the other models, provides a valuable unavailability model for decision making in the context of test and maintenance activities. Finally, this paper specifically focuses on aging PSA for critical components within a subsystem. However, to comprehensively assess the aggregate effects of aging, test-caused degradation, and maintenance effectiveness on plant-specific results, future work should incorporate plant-specific data and consider all critical components.
Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References