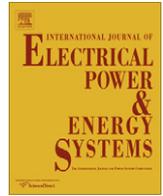




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A time-varying transformer outage model for on-line operational risk assessment

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ABSTRACT

The failure probabilities of system components may vary with changes in the operating conditions. Performing a probabilistic risk assessment in real-time is challenging, since component failure probabilities are difficult to predict. Accordingly, this paper introduces a delayed semi-Markov process that incorporates real-time data from advanced sensors, as a means of efficiently calculating time-varying or condition-based failure probabilities. To demonstrate the feasibility of the procedure, a time-varying transformer outage model with numerical examples is presented. In the proposed technique, an analytic random model is developed to accommodate the impact of real-time dissolved gas analysis data, as well as other conditions pertaining to the failure probabilities of system components.

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1. Introduction

In order to operate a power system with a smaller security margin that meets essential economic specifications in the power market, more refined methods are required for dealing with uncertain variables in power system security assessments. A probabilistic risk assessment (PRA) program is a useful tool for system operators to carry out risk assessments [1]. There has been some research on security assessments, using risk indices that can quantify the likelihood and severity of the contingencies [2–8].

Probability-based reliability assessments for generation and transmission are already well developed for system planning purposes [9–14]. However, there are fundamental differences between system planning and system operations, and one of the most important of these lies in the modeling of component outage. The objective of on-line operational risk assessments is to use currently available information to predict operational risk, and take appropriate operational measures to deal with upcoming system states over a short-term time frame (minutes or hours). In contrast, reliability assessments for system planning are concerned with making decisions on system enhancements over a long-term time frame (years) [15].

The component outage data used in traditional reliability evaluations are usually average values based on long-term statistical records [9,10]. However, this type of long-term average outage data is not suitable for real-time operational risk assessments, since the operating conditions of system components (such as

external environment and internal deterioration) change occasionally under real-time conditions, and this affects the failure probabilities of the system components. Hence, a time-varying outage model of the components should be both useful and appropriate. As a particular example, this paper presents a time-varying transformer outage model, and its feasibility is demonstrated.

Utilities perform preventive maintenance (PM) on their assets in order to maximize their long-term profits, while delivering high-quality service to their customers with acceptable and manageable risks. The operating parameters of transformers are periodically recorded during maintenance, and the resulting data can be used to predict transformer failure probabilities, and applied in reliability-centered maintenance (RCM) [16–19].

It has been more than forty years since on-line transformer-monitoring and fault-diagnosis applications were first introduced in electric power systems [20–23]. These applications are capable of continuously monitoring and analyzing transformer operating conditions. They can detect changes in the operating conditions based on a historical database, and identify potential problems before they become catastrophic. The relevant techniques include dissolved gas analysis (DGA), analyses of partial discharge (PD), hottest spot temperature (HST), and winding deformation [24–27]. Among these, DGA has gained worldwide acceptance as a means of detecting incipient faults, and is widely used. Both IEC [28] and IEEE [29] have issued reference guides for the interpretation of DGA data.

On-line monitoring data with precise time stamps can be used to predict component failure probabilities. In this paper, DGA data are used to formulate a transformer outage model, and the model is then applied to operational risk assessments. Other useful data

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Nomenclature

$X(t)$	state of component at time t	λ	failure rate
$P\{\mathcal{O}\}$	probability of event \mathcal{O}	μ	repair rate
$P_i(t) = P\{X(t) = i\}$	probability of component being in state i at time t	$A(t)$	instantaneous availability of component at time t
		$U(t)$	instantaneous unavailability of component at time t

obtained from on-line monitoring systems can also be incorporated into the proposed technique.

The paper is organized as follows. In Section 2, a delayed semi-Markov process model is proposed, and is used to formulate a time-varying outage model. As an illustration, this method is used to calculate time-varying transformer failure probabilities. A technique for estimating the transformer failure rate from on-line monitoring data is described in Section 3. In Section 4, a numerical example is presented to demonstrate the proposed model. Conclusions are stated in Section 5.

2. Delayed semi-Markov model

2.1. Problems arising in operational risk assessments

Traditional reliability evaluations use steady-state failure probabilities calculated from long-term statistical records. However, in on-line operational risk assessments, time-varying failure probabilities should be used.

A two-state Markov process model (shown in Fig. 1) is widely used in reliability assessments [10,11].

Here λ denotes the component failure rate and μ is the repair rate. This is a homogenous Markov process with discrete states [30], and can be formulated in terms of the Fokker–Planck equation [31]:

$$\left[\frac{dP_0(t)}{dt} \quad \frac{dP_1(t)}{dt} \right] = [P_0(t) \ P_1(t)] \begin{bmatrix} -\lambda & \lambda \\ \mu & -\mu \end{bmatrix} \tag{1}$$

where $P_0(t)$ is the probability of being in state 0 (normal operating state) at time t , and $P_1(t)$ is the probability of being in state 1 (outage state) at time t . If the component is initially in state 0, then $P_0(0) = 1$. Considering the boundary condition $P_0(t) + P_1(t) = 1$, $P_0(t)$ and $P_1(t)$ can be calculated from and Eq. (1):

$$\begin{cases} P_0(t) = \frac{\mu}{\lambda + \mu} + \frac{\lambda}{\lambda + \mu} e^{-(\lambda + \mu)t} \\ P_1(t) = \frac{\lambda}{\lambda + \mu} - \frac{\lambda}{\lambda + \mu} e^{-(\lambda + \mu)t} \end{cases} \tag{2}$$

The component failure probability curve $P_1(t)$ is shown in Fig. 2. As $t \rightarrow \infty$, $P_1(t) = \frac{\lambda}{\lambda + \mu} = \bar{P}_1$, where \bar{P}_1 is the steady-state failure probability used in traditional reliability assessments, and referred to as the unavailability U .

In on-line operational risk assessments, $P_1(T_m)$ should be used in place of \bar{P}_1 as the failure probability for predicting operational risk for the upcoming system state at T_m , as shown in Fig. 2.

It should be noted that the failure rate λ and the repair rate μ in Eq. (1) are regarded as constants. From the on-line operational point of view, the failure rate varies according to weather, age, and other operating conditions. For example, the failure probability of transmission lines could be much higher in extreme weather

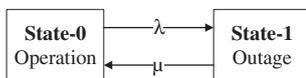


Fig. 1. State space of a two-state Markov process model.

conditions [32]. The failure probability of a transformer increases as the transformer deteriorates [33].

In the following subsections, we develop a delayed semi-Markov model for transformer failure that can accommodate varying operational conditions.

2.2. Classification of transformer faults

There are various types of faults that cause transformer failure, and they can be roughly divided into two categories: internal latent faults and external random faults. The details of various transformer faults are listed in Table 1.

The internal latent faults can be categorized into aging failures and man-made hidden problems. The internal latent faults can be diagnosed and monitored by many techniques, including dissolved gas analysis (DGA). The internal latent failure rate can be approximately predicted using the measured data from an on-line monitoring system.

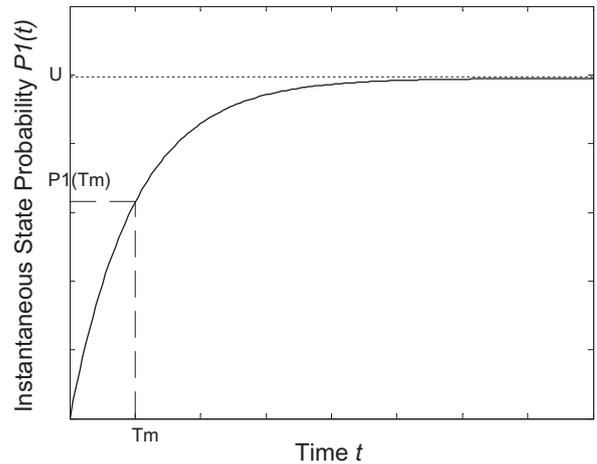


Fig. 2. Graph of transient state probability.

Table 1
Classification of transformer faults.

Classification	Details
<i>Internal latent faults</i>	
Aging failure	(1) Winding insulation failure due to age (2) Insulation oil deterioration (3) Winding structure distortion (4) Rust or joint abrasion with joint deterioration, etc.
Man-made hidden problems	(1) Improper design or installation (poor installation of core lamination, sharp-angled tubing in the trunk, which reflects on partial discharge, etc.) (2) Improper maintenance (allowing air bubbles in the insulation oil, shoddy repairs, etc.).
<i>External random faults</i>	(1) Operator error (2) External insulation failure caused by lightning, etc.

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