MODEL-BASED OPTIMIZATION FRAMEWORK USING PREDICTIVE HEALTH MODEL FOR ASSET MANAGEMENT

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ABSTRACT

In this paper, a model-based predictive framework is used to optimize the operation and maintenance actions of power system equipment based on the predicted health state of this equipment. In particular, this framework is used to predict the health state of transformers based on their usage and operating environment. The health state of a transformer is hereby given by the hot-spot temperature of the paper insulation of the transformer and is predicted using the planned loading of the transformer. The actual loading of the transformer is subsequently optimized using these predictions.

INTRODUCTION

Reliability of the electrical infrastructures is becoming an important issue as a significant portion of the electricity grid is reaching the end of its operating age within coming decades. Current asset management is based on the condition of the infrastructure. The condition based asset management uses this condition information of the infrastructure to maintain and manage the electrical equipment [1]. Ageing models of the equipment are available or are being developed which can estimate the health state of the equipment based on the condition information. A model, which can be used to predict the health state of the equipment based on the condition and the usage of the equipment, is required in order to ensure optimal utilization of the equipment [2].

In [2], a framework was proposed for modelling the health state of power system equipment and used for modelling degradation of the paper insulation of transformers. This framework can be used to predict the effects of different maintenance actions and usage patterns. The predictions can then be used for the optimization of maintenance actions and the equipment usage. In this paper, we use this framework to optimize the loading of the transformer using temperature predictions.

The hot-spot temperature of the transformer can be used to determine the loading limits [3, 4]. This hot-spot temperature can be predicted using the load of the transformer [3-7].

FRAMEWORK FOR MODEL-BASED OPTIMIZATION

A framework for model-based optimization consists of a predictive health model [2]. The framework also defines the cost function for the optimization. Below the components of this framework are outlined briefly.

Predictive health model

The predictive health model in the framework includes a dynamic stress model, a failure model and an estimation of cumulative stresses, as illustrated in Fig. 1. As equipment ages, various stresses, such as electrical, thermal, mechanical and environmental stresses, weaken the strength of the equipment. The cumulative stresses of the equipment are affected by the usage pattern (e.g., the loading) and the maintenance actions (e.g., the replacement of parts) performed on the equipment. The health state of the equipment is represented by the cumulative stresses. Their dynamics can be described using a dynamic stress model such as the following discrete-time state-space model:

$$\hat{\mathbf{x}}(k+1)=\mathbf{f}\left(\hat{\mathbf{x}}(k),\mathbf{u}(k)\right), \tag{1}$$

where $\mathbf{u}(k)=\left[u_{\mathrm{a}}(k) \quad u_{\mathrm{d}}(k)\right]^{\mathrm{T}}$. At discrete time step k, the future cumulative stresses $\hat{\mathbf{x}}(k+1)$ are predicted based on the usage of the equipment $\mathbf{u}_{\mathrm{d}}(k)$, the maintenance actions $\mathbf{u}_{\mathrm{a}}(k)$ and the current cumulative stresses $\hat{\mathbf{x}}(k)$.

As the cumulative stresses increase over time, the probability of failure of the equipment also increases. The relationship between the cumulative stresses and the failure rate of the equipment is described in a failure model. The failure model uses the predicted cumulative stresses to predict the failure rate of the equipment. The failure model directly maps the cumulative stresses to the failure rate $\hat{y}(k)$ as follows:

$$\hat{y}(k)=g\left(\hat{\mathbf{x}}(k)\right). \tag{2}$$

The cumulative stresses are indicated by condition parameters of the equipment, such as the partial discharge, temperature measurements, etc. Different online and offline monitoring systems can detect these condition

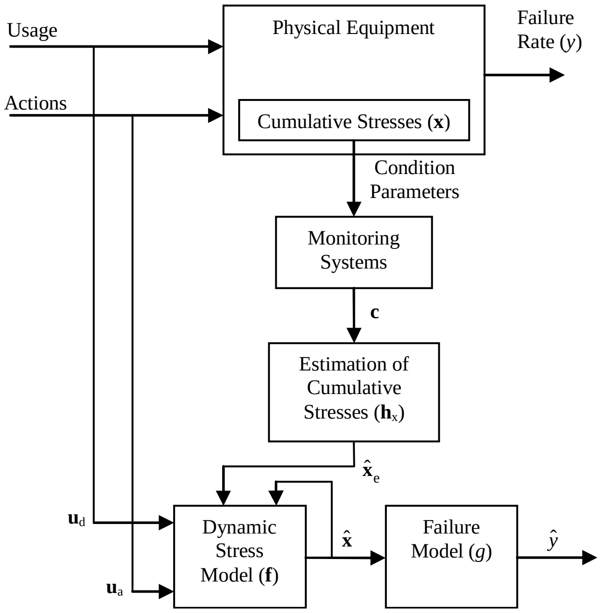

Fig. 1. Predictive health model which predicts cumulative stresses and failure rate for the given usage and actions.

parameters. In practice, only a few condition parameters (such as the electrical and thermal stresses) are measured by monitoring systems. Estimates of the monitored cumulative stresses $\hat{\mathbf{x}}_{\mathrm{e}}(k)$ can be made based on measurements $\mathbf{c}(k)$ of the monitoring systems as follows:

$$\hat{\mathbf{x}}_{\mathrm{e}}(k)=\mathbf{h}_{\mathrm{x}}(\mathbf{c}(k)). \quad (3)$$

The estimated cumulative stresses $\hat{\mathbf{x}}_{\mathrm{e}}(k)$ can be used in the dynamic stress model to update the corresponding cumulative stresses $\hat{\mathbf{x}}(k)$. The remaining unmonitored cumulative stresses are predicted by the dynamic stress model.

Optimization of maintenance and usage

Typically, maintenance improves the health state of the equipment, which, in turn, reduces its failure rate. An optimal maintenance action balances the economical cost of the maintenance, the improvement of the health state and the reduction in the failure rate of the equipment. The usage indicates its utilization.

The total cost of the usage and the maintenance actions consist of three sub-cost functions. The sub-cost function of the planned usage and the maintenance actions J_{a} incorporates the economical cost of the maintenance. The sub-cost function of the failure rate J_{f} takes into account the cost associated with the failure of the equipment. The sub-cost function of the cumulative stresses J_{cs} incorporates the cost of the deterioration of the equipment. The summation of these three sub-cost functions gives the total cost of a particular maintenance action in a particular state.

The optimization of the usage and the maintenance actions is considered over a given predicted time frame of N steps in the future, such that future usage and future maintenance actions can be optimized. The total cost over the predicted time frame is considered in the optimization. Hence, the model-based optimization problem is formulated as follows:

$$\begin{aligned}\min_{\mathbf{u}(k),\cdots,\mathbf{u}(k+N-1)} & \left[\sum_{l=0}^{N-1} J_{\mathrm{a}}\left(\mathbf{u}(k+l)\right)\right] \\ & +\left[\sum_{l=0}^{N-1} J_{\mathrm{f}}\left(\hat{y}(k+l)\right)\right] \\ & +J_{\mathrm{cs}}\left(\hat{\mathbf{x}}(k+N)-\hat{\mathbf{x}}(k)\right) \quad (4)\end{aligned}$$

subject to

$$\hat{\mathbf{x}}(k+l+1)=\mathbf{f}\left(\hat{\mathbf{x}}(k+l),\mathbf{u}(k+l)\right)$$
$$\hat{y}(k+l)=g\left(\hat{\mathbf{x}}(k+l)\right) \qquad \text{for } l=0,\cdots,N-1.$$

The predictive health model is thus used to predict the cumulative stresses and the failure rates for the planned usage and different future maintenance actions. The total cost is evaluated for different future usage and maintenance actions over the predicted time frame. The optimal usage and maintenance actions minimizing the total cost over the time horizon is searched for.

PREDICTIVE HEALTH MODEL OF TRANSFORMER

The model-based optimization framework is implemented on a case study of the loading of transformers. The temperature rise, due to the loading, degrades the paper insulation of the transformer. This degradation process reduces the dielectric and mechanical strength of the insulation paper and hence reduces its life time [2-4, 8].

In order to determine the loading of the transformers, the hot-spot temperature is considered. The hot-spot temperature is defined as the temperature of the hottest part of the windings of the transformer. It is this temperature that is used for determining the level of the paper degradation.

Thermal model of a power transformer

The thermal models of a power transformer are based on the ambient temperature, the top-oil or bottom-oil temperatures and the hot-spot temperature. The oil temperatures are calculated based on the ambient temperature and on the dynamics of the heat transfer from the oil to the environment through the radiators. Similarly, the hot-spot temperature is calculated based on the oil temperatures and on the dynamics of the heat transfer between the windings and the oil.

IEEE C57.91 [4] suggests a top-oil time constant based on the mass of different parts and on the cooling type of the transformer. The winding time constant, which describes the dynamics of the heat transfer between the windings and the oil, is estimated based on the cooling experiments. Swift et al. [5] propose a thermal model based on heat transfer theory, which includes thermal capacitances and non-linear thermal resistances. Their approach is extended by Susa et al. [6, 7] by considering the oil viscosity changes and the loss variation with the temperature. Their thermal model consists of the top-oil model and the hot-spot model.

The top-oil model and the hot-spot model are converted to the dynamic stress model (1) of the model-based optimization framework. The top-oil temperature and the hot-spot temperature are taken as cumulative stresses. The load factor is taken as the usage. The ambient temperature is taken as the exogenous input. The differential equations of the top-oil model and the hot-spot model are discretized by using the forward Euler approximation [9].

LOADING OF TRANSFORMER BASED ON THE HOT-SPOT TEMPERATURE

The maximum allowable loading of a transformer mainly depends on the thermal performance of the transformer. IEEE C57.91 [4] defines four types of loading based on maximum hot-spot temperature.

Under normal life expectancy loading, the maximum hot-spot temperature allowed is 120 °C. Planned loading beyond nameplate (130 °C) is suggested for a planned, repetitive load, provided that the transformer is not loaded continuously at the rated load. Long-time emergency loading (140 °C) is suggested only for rare emergency conditions. Short-time emergency loading (180 °C) is only suggested for a short time in a few abnormal emergency conditions. Normal life expectancy loading is considered risk free [4]. In the other three cases, the calculation of the loss of life due to the loading and the risk of failure associated with this should be considered.

The type of loading and the allowed limits depend on the preference of the utilities, the criticality of the transformer and the situation (e.g., under emergency conditions limits may be relaxed). The normal life expectancy loading based on the hot-spot temperature prediction is considered in this section.

The load of the transformer depends on the energy demand and production. A prediction of the load can be made based on the predicted generation, the predicted loading and the network configuration. For the predicted loading, the hot-spot temperature should be below the maximum value of 120 °C for the normal life expectancy loading. In the case of thermal overloading of the transformer, the load should be reduced. The load can be varied using different methods, such as network re-configurations, changing the generation and the load, using an energy storage, etc.

In our framework, the required loading is considered as reference loading $u_{\mathrm{I,ref}}$. The actual loading of the transformer u_{I} should follow the reference loading within the given thermal limit of the transformer. Assuming the loading u_{I} to be controllable, the optimization problem is specified as:

$$\min_{u_{\mathrm{I}}(k),\cdots,u_{\mathrm{I}}(k+N-1)} \sum_{l=0}^{N-1} \left[u_{\mathrm{I}}(k) - u_{\mathrm{I,ref}}(k)\right]^2 \qquad (5)$$

subject to

$$\frac{1+R\cdot u_{\mathrm{I}}(k)^2}{1+R}\cdot\mu_{\mathrm{pu}}(k)^n\cdot\Delta\theta_{\mathrm{oil,rated}} = \mu_{\mathrm{pu}}(k)^n\cdot\tau_{\mathrm{oil,rated}}\cdot\frac{x_{\theta,\mathrm{oil}}(k+1)-x_{\theta,\mathrm{oil}}(k)}{h} + \frac{\left(x_{\theta,\mathrm{oil}}(k)-u_{\theta,\mathrm{amb}}(k)\right)^{n+1}}{\Delta\theta_{\mathrm{oil,rated}}{}^{n}} \qquad (6)$$

$$u_{\mathrm{I}}(k)^2\cdot P_{\mathrm{cu,pu}}(k)\cdot\mu_{\mathrm{pu}}(k)^n\cdot\Delta\theta_{\mathrm{hs,rated}} = \mu_{\mathrm{pu}}(k)^n\cdot\tau_{\mathrm{wdg,rated}}\cdot\frac{x_{\theta,\mathrm{hs}}(k+1)-x_{\theta,\mathrm{hs}}(k)}{h} + \frac{\left(x_{\theta,\mathrm{hs}}(k)-x_{\theta,\mathrm{oil}}(k)\right)^{n+1}}{\Delta\theta_{\mathrm{hs,rated}}{}^{n}} \qquad (7)$$

$$x_{\theta,\mathrm{hs}}(k+l)\le 120^\circ\mathrm{C} \qquad \text{for } l=0,\cdots,N-1,$$

where $x_{\theta,\mathrm{oil}}$ and $x_{\theta,\mathrm{hs}}$ are top-oil temperature and hot-spot temperature, respectively. Equations (6) and (7) are given by the top-oil model and the hot-spot model, respectively [9]. The time step for discretization is given by h.

The optimization problem (5) consists of non-linear constraints. The optimization therefore is solved by a non-linear solver, SNOPT [10]. This solver is used through the Tomlab v6.1 [11] interface in Matlab v7.5.

Simulation of loading based on the hot-spot temperature

The 250 MVA transformer mentioned in [3, 6, 9] is considered for the case study. An initial hot-spot temperature of 59.4 °C, an initial top-oil temperature of 49.8 °C and ambient temperature of 25 °C are assumed for the case studies.

Optimization of the load given in (5) has been applied for the transformer. A time step h of 1 minute is considered for the discretization. A prediction horizon N of 15 minutes is considered for the optimization. At each time step, the hot-spot temperature is predicted for the given prediction horizon. The optimal load profile is recommended based on the prediction. The load of the

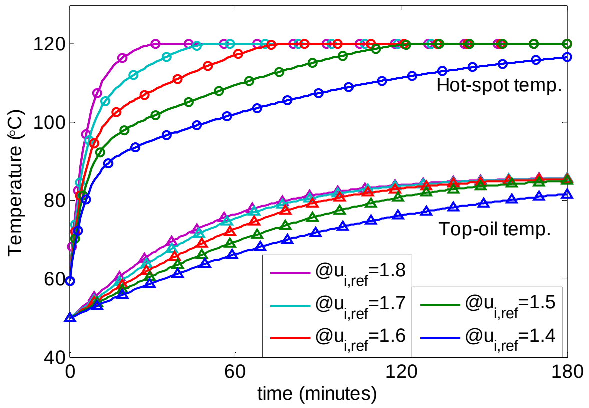

Fig. 2. Hot-spot and top-oil temperatures with load control. For all the loadings, the hot-spot temperature is maintained below the limit of 120 °C.

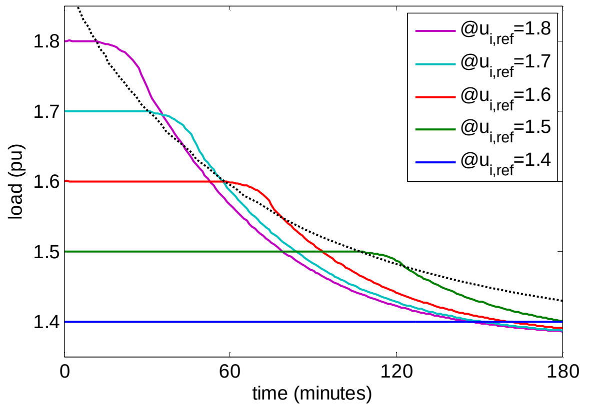

Fig. 3. Load profile for the proposed load control. The dashed line shows the starting of the adjustment of the load.

transformer is adjusted based on the recommended profile. Reference loadings in the range of 1.4 p.u. to 1.8 p.u. are considered. Each loading is applied for a duration of 180 minutes. The temperatures and the load are shown in Fig. 2 and Fig. 3, respectively. As seen in these figures, the hot-spot temperature is kept below the limit by lowering the load of the transformer. The dashed line in Fig. 3 indicates the starting of the adjustment of the transformer load.

CONCLUSIONS AND FUTURE WORK

A model-based predictive optimization framework has been applied for the optimization of the loading of a transformer. By using the optimized loading profile, the hot-spot temperature was maintained below the allowed limit. The proposed method optimizes the utilization of the transformer by recommending load changes when required. The dynamic rating of the transformer is achieved without exceeding the safety limit of the hot-spot temperature.

The framework will be extended to include the load control of the transformers in the network. The optimal loading of the transformers will be maintained by performing an optimal power flow (OPF) computation of the network. The reactive power control, the tap control and the consumer load control will be considered in the optimal power flow computation.

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