Health Index, Risk and Remaining Lifetime Estimation of Power Transformers

J. Foros and M. Istad

***Abstract*— A new method for systematically estimating health index, probability of breakdown and remaining life for power transformers is presented. The method combines three basic models; a physical winding degradation model, a health index model based on condition monitoring data combined with expert judgement, and a statistics-based end-of-life model. The statistics-based model uses data from a database of scrapped transformers under development in Norway. Combining the first two models with the statistics-based model, an individual and condition-dependent probability of breakdown is obtained. From this, the expected remaining life is calculated. Finally, the stochasticity of the method is utilized for optimization of maintenance and replacement. The method hence provides key decision support for transformer managers, enabling them to identify transformers in poor condition, and to follow-up and prioritize transformers for maintenance and replacement. The proposed method has been implemented in a transformer asset management tool for Norwegian utilities. The usefulness of the method is illustrated by applying it to selected transformers from one of these utilities. Finally, important limitations, uncertainties and further improvements are discussed.**

***Index Terms* — Condition monitoring, degradation, health index, lifetime estimation, power transformers, maintenance optimization, risk analysis**

I. Introduction

THE Norwegian transformer fleet is aging and has an average age of about 32 years, and approximately 15% are over 50 years old. The design lifetime for transformers at rated load is of the order of 30 years. The average transformer in Norway has thus achieved life expectancy under rated load. However, as most transformers in Norway operate under lower load than rated with excellent cooling conditions, life expectancy is probably significantly higher. There is therefore a potential for utilizing the transformers beyond their original life expectancy, thereby postponing costly replacements. This should be done in a controlled way with continuous analysis and follow-up of the transformer condition, to ensure that transformers in poor condition are identified and replaced prior to breakdown.

Based on present statistics and costs, the cost of replacing all transformers in Norway with an age of 50 years or above is estimated to 1.8 billion NOK (approx. 200 million USD). If instead, due to improved analysis and follow-up of the transformer condition, half of these transformers can safely stay in operation for 20 more years, the total positive present value of postponed replacement amounts to 800 million NOK (approx. 100 million USD).

For quantitative analysis of transformer condition and remaining lifetime, three popular basic approaches stand out: Degradation modeling, condition assessment from monitoring data, and statistical end-of-life modeling. The first approach employs a physical model that estimates the degradation and remaining life of the insulation paper using historic operational data. The second approach assesses condition monitoring data (such as data from oil tests and visual inspections) and typically aggregates this information into a quantitative measure of present condition (a health index). This approach may be based on advanced mathematical modelling, but typically also requires some degree of expert judgement. The third approach is an evaluation of the expected remaining life of the transformer from its current age, by comparison with statistical data (combined with expert judgement if statistical data is scarce). There are advantages and disadvantages with each of these three approaches. The first approach enables calculation of remaining life but does not consider condition monitoring data. The second approach enables all present condition monitoring data to be included but estimating remaining life from this is challenging. The last approach enables a stochastic model to be built with the use of statistics but does not reflect any other data than the transformer age. The validity of this approach depends on the quality and representability of the available statistical data.

Several methods for analyzing transformer condition and remaining lifetime, that in various ways include or combine some of the three above approaches, have been proposed in the literature. Some early examples of health index models are those of Dominelli *et al.* [1], Anders *et al*. [2] and Jahromi *et al.* [3]. Later advancements that combine degradation, condition and/or statistical models have been proposed by e.g. Jarman *et al*. [4], Vermeer *et al*. [5] and Picher *et al.* [6]. More recently, research has been focusing on lifetime estimation [7, 8], feature selection methods [9, 10], and ways to aggregate information from different condition measurements. For the latter topic, methods that utilize e.g. fuzzy theory [11, 12], Markov chains

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[13], Bayesian belief networks [14] and machine learning methods [15, 16] have been suggested. However, less work has been done on applying such information to suggest or optimize maintenance and replacement decisions [17].

This paper presents a new method for power transformer assessment combining all the three above basic approaches. The method allows for all available relevant data to be combined into a quantitatively estimated probability of breakdown, from which the transformer remaining life is calculated. The developed method takes advantage of data from a database of scrapped transformers under development in Norway. Since the method is probabilistic, it also enables optimization of maintenance and replacement, thus providing key decision support for transformer managers. The method is developed for power transformers of or above 22 kV with mineral oil and cellulose paper as insulation, of both network and generator step-up type.

II. Overall Method

The overall flow diagram of the method is shown in Fig. 1. The method consists of three basic models; a winding degradation model, a condition model, and a statistics-based end-of-life model, that together feed a risk model and a maintenance and replacement analysis.

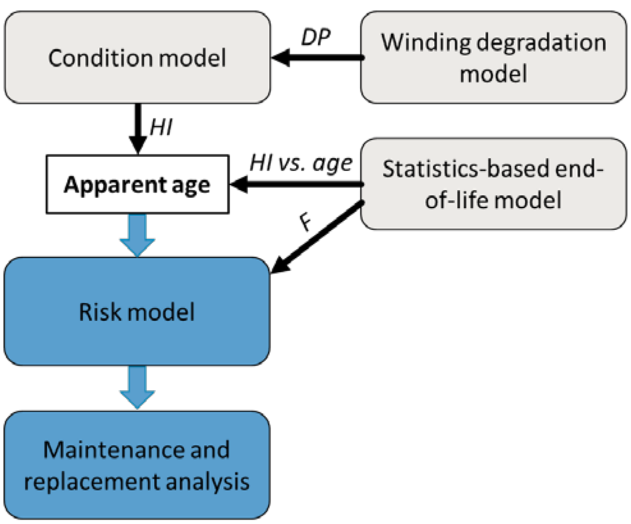

Fig. 1. Overall flow diagram for the proposed method. The three basic models return the transformer degree of polymerization (DP), the transformer health index (HI), and statistics from the scrapping database (a failure probability distribution F and health index as a function of age). They are linked through a so-called apparent age, that is utilized in the risk model.

The degradation model uses historic load and temperature data to estimate the degree of polymerization (DP) for the insulation paper, which is related to the paper's mechanical strength. The paper strength is widely regarded as the ultimate life limiting factor for transformers. The condition model estimates a health index from all available data for the current condition of the transformer, including the calculated DP-value. The statistics-based model extrapolates historic scrapping data for several transformers to estimate a transformer end-of-life distribution. By relating the calculated health index of the transformer in question to the statistics for the population of scrapped transformers, the *condition-dependent* probability of breakdown and remaining life are estimated. Finally, the profitability and optimal timing of maintenance or replacement is analyzed.

The condition model can be based on any data that reflects the transformer condition and hence its probability of breakdown. However, quantitative condition data at Norwegian utilities today are primarily data related to the active part - core, windings and oil - most importantly periodic oil test data such as dissolved gas concentrations and water content. Other data, such as online condition data or condition data for other parts than the active part are at present available only to a limited extent. The method is therefore presented only for the active part of the transformer.

The statistics-based model uses scrapping data instead of failure statistics, since good failure statistics for transformers are not available in Norway today. In addition, available failure statistics from other countries have previously been shown to be poorly suited for establishing a stochastic lifetime model, since these statistics tend to show little increase in failure rate with age [18]. This is probably partly due to preventive replacement and that many transformers have yet to reach an old age. The quality of the scrapping database, and how representative it is for the transformer to be analyzed is important for the reliability of the results. At present, the number of transformers in the database is quite limited, and hence, the method cannot currently be expected to be generally applicable for all transformers in Norway. This, however, will improve as the database increases. Due to the limited statistical basis, the proposed method also does not differentiate between different types of transformers, such as network and generator step-up transformers. One exception from this is the winding degradation model, which differentiates between standard (Kraft) insulation paper and thermally upgraded (Insuldur) paper.

Risk is given by the probability of failure combined with the consequences of failure. The probability of failure is estimated using the statistics-based model and by modeling the active part of the transformer as a non-repairable component. This simplification is justified by the fact that repair of the active part is difficult and costly, and either is not done or when it's done returns the transformer to an almost new condition. Hence, in this method, the consequence of a failure is full transformer breakdown so that its needs to be replaced. The consequences of breakdown are included in terms of financial costs.

Each part of the proposed method is explained in detail in the following three sections, before an example of application of the method is given in section VI.

III. Basic Models

A. Winding degradation

The insulation paper in transformer windings degrades over time due to the cellulose molecules decomposing to shorter molecules. The length of the molecules can be expressed as a degree of polymerization (DP), which is the average number of monosaccharide units in the molecules. Insulation with short

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molecules have less mechanical strength, and hence is more prone to failure if the transformer is exposed to mechanical stress such as a short-circuit. A DP-value of 200 is commonly taken as the end-of-life criterion for the paper and thus the transformer. The DP-value can be measured in a laboratory, but this requires a paper sample to be taken from the windings, which is usually not feasible when the transformer is in operation. Estimating the DP-value based on the historic loading of the transformer is an alternative approach. The change in DP over some time period can be described by [19]

$$\frac{1}{DP_{\text{end}}} - \frac{1}{DP_{\text{start}}} = \int_{\text{start}}^{\text{end}} \mathrm{d}t \; A(t) e^{-E_a/RT(t)} \tag{1}$$

where DP_{start} and DP_{end} are the DP-values at the start and end points of the time period, t is the time, $A(t)$ is an environment factor that depends on the moisture and oxygen content in the oil, E_a is the activation energy, R is the universal gas constant, and $T(t)$ is the temperature to which the paper is exposed. The parameters $A(t)$ and E_a have been estimated in laboratory experiments both for standard Kraft paper and thermally upgraded Insuldur paper [20]. In this paper, (1) is used to calculate the present DP-value from the DP-value when the transformer was commissioned, which typically is around 1000. A discretization of (1) into hours is sufficient, as daily temperature variations then are included. Note that (1) is a simplification that will give conservative results, i.e. overestimate the rate of degradation. If better precision is required, a more advanced model can be consulted [21, 22].

There are typically strong temperature gradients in transformers, and this causes the DP-value to vary within the transformer. For condition monitoring purposes it is desirable to estimate the DP-value at the location in the transformer where the paper degrades fastest, i.e. at the winding temperature hot-spot. For some new transformers, the hot-spot temperature to be included in (1) is measured directly using fibre-optic sensors. For older transformers the hot-spot temperature must be estimated from other temperature measurements such as top oil temperature or ambient temperature. Using the IEC temperature model [23], while for simplicity assuming that the load varies slowly enough that the transformer is approximately in steady state, the hot-spot temperature T_{hs} is given by

$$T_{hs} = T_a + \Delta T_{to-a} \left(\frac{1 + RK^2}{1 + R} \right)^x + H g_r K^y \tag{2}$$

in terms of the ambient temperature T_a. Here ΔT_{to-a} is the top oil temperature rise above ambient temperature at rated load, H is the hot-spot factor, g_r is the average winding temperature rise above average oil temperature at rated load, K is the load factor (load current/rated current), R is the ratio of load losses at rated current to no-load losses, and x and y are the oil and winding exponents, respectively. The constants in (2) depend on the cooling mode of the transformer (e.g. ONAN, ONAF etc.) and can be found from the transformer's temperature rise test.

B. Condition model: Health index

The condition model could be designed to give the transformer failure probability directly, based on an assessment of all relevant failure modes. Such a model would require quantification of the probability of occurrence of each failure mode from observable condition data. This poses a huge challenge as it requires a lot of unknown data, and is therefore left for further work when data availability improves. Here, a different approach is chosen in which a health index is instead derived from assessment of condition data, and the failure probability is next derived from the health index with the aid of statistics (see next section). Knowledge of failure modes and their criticality are used to weight the importance of each type of condition data for the health index. Such a health index model must be designed to meet some criteria: 1) The health index reflects the probability of failure and is both lower and upper bound, 2) Any relevant condition data can be included, 3) Poor condition data are not masked by aggregation, i.e. the health is never better than that indicated by the worst condition data.

The proposed health index (HI) model hence reads

$$HI = \prod_{j=1}^{n} \left(1 - R_j(\theta_j)\right), \tag{3}$$

where $R_j(\theta_j)$ is a function describing the effect on the health index of condition data j on a scale from 0 to 1, θ_j is the assessed grade of condition data j, and n is the total number of condition data. The health index is a number between 0 and 100%, where 100% represents a perfect condition. The form of the health index function is derived as an analogy to a fault tree model with a single OR-gate between the top event and its basic events. The model assumes for simplicity that all condition data are independent.

In addition to being bound between 0 and 1, $R_j(\theta_j)$ should be monotonically increasing (or alternatively decreasing). Hence, $R_j(\theta_j)$ may be suitably represented by a sigmoid function. Furthermore, defining the function piecewise makes it easier to tune it according to which condition data j it represents. For condition data where an increasing grade θ_j signifies a deteriorating condition, the function $R_j(\theta_j)$ is therefore defined as

$$\begin{aligned} R_j(\theta_j) &= R_{j,r} \cdot (1 + r_{j,b})^{\theta_j - \theta_{j,r}} && \theta_j \le \theta_{j,r} \\ R_j(\theta_j) &= R_{j,m} - (R_{j,m} - R_{j,r}) \\ &\quad \cdot (1 + r_{j,w})^{-(\theta_j - \theta_{j,r})} && \theta_j > \theta_{j,r} \end{aligned} \tag{4}$$

Here $\theta_{j,r}$ is a reference condition that must be specified, $R_{j,r}$ is the effect on the health index of the reference condition ($0 < R_{j,r} \le 1$), $R_{j,m}$ is the maximum effect on the health index ($R_{j,r} \le R_{j,m} \le 1$), and $r_{j,b}$ is the rate of change of $R_j(\theta_j)$ per unit of θ_j when θ_j is below $\theta_{j,r}$. The constant $r_{j,w}$ specifies the increase of $R_j(\theta_j)$ when θ_j is above $\theta_{j,r}$ and is for $r_{j,b} \ll 1$,

$r_{j,w} \ll 1$ and $R_{j,m} \neq R_{j,r}$ approximated as

$$r_{j,w} = r_{j,b} \frac{R_{j,r}}{R_{j,m} - R_{j,r}} \quad (5)$$

by requiring that the derivative of $R_j(\theta_j)$ is continuous for $\theta_j = \theta_{j,r}$. The above definition of the function $R_j(\theta_j)$ implies that the reference condition is the condition at which $R_j(\theta_j)$ increases most rapidly. It also ensures that $R_j(\theta_j)$ approaches 0 as θ_j decreases towards minus infinity, and 1 as θ_j increases towards infinity, as required. Hence, a perfect condition state θ_j in this model is represented as minus infinity.

For some condition data, a decreasing grade rather than an increasing grade signifies a deteriorating condition. For such data, the function $R_j(\theta_j)$ is defined as

$$\begin{aligned} R_j(\theta_j) &= R_{j,r} \cdot (1 + r_{j,b})^{-(\theta_j - \theta_{j,r})}, \qquad \theta_j \geq \theta_{j,r} \\ R_j(\theta_j) &= R_{j,m} - (R_{j,m} - R_{j,r}) \\ &\qquad \cdot (1 + r_{j,w})^{\theta_j - \theta_{j,r}}, \qquad \theta_j < \theta_{j,r} \end{aligned} \quad (6)$$

The parameters for the function $R_j(\theta_j)$ depend on the condition data j that it represents. All the condition data that are included in the health index are listed in TABLE I, with a suggested specification of $R_j(\theta_j)$. For the parameters from the oil tests, the grading θ_j follows the standard IEC 60422 [24] and CIGRÉ report 443 [25]. The tuning parameters $R_{j,r}$ and $R_{j,m}$ serve to weight the importance of the different condition data. These have been set with expert judgement based on knowledge on how the data relate to failure modes, motivated by [24, 25, 26]. Therefore, the DP-value and the gas concentrations are set to be more important than the oil parameters in TABLE I. The last tuning parameter $r_{j,b}$ has been set to 1 for all parameters from the oil test, which means that $R_j(\theta_j)$ doubles for each increment in θ_j. For the DP-value, a value of 0.01 for $r_{j,b}$ ensures that $R_j(\theta_j)$, and hence the effect on the health index, remains small until the DP-value is significantly reduced. This is because the DP-value must be relatively low before it is expected to affect the failure probability. The tuning parameters are hard to validate, as the health index cannot be measured directly. All tuning parameters should in future work be benchmarked and adjusted based on testing of the health index model on a selected transformer population, in collaboration with transformer experts at utilities.

For the dissolved gases ($j = 1$ to 7), both the gas concentration and the gas concentration increase is included in the model, and for each dissolved gas, the grade θ_j is conservatively determined by

$$\theta_j = \max(\theta_{\mathrm{j,c}}, \theta_{\mathrm{j,ci}}), \quad (7)$$

where $\theta_{\mathrm{j,c}}$ is the grade for the gas concentration and $\theta_{\mathrm{j,ci}}$ is the grade for the gas concentration increase.

TABLE I
SPECIFICATION OF $R_j(\theta_j)$ FOR ALL THE CONDITION DATA THAT ARE INCLUDED IN THE HEALTH INDEX.

j	Condition data	Specification of $R_j(\theta_j)$
1	H2	$\theta_j = -\infty, 1, 2, 3, 4, 5$ (perfect condition: $-\infty$)
2	CH4	$\theta_{j,r} = 5$
3	C2H6	$R_{j,r} = 0.5$
4	C2H4	$R_{j,m} = 0.5$
5	C2H2*	$r_{j,b} = 1$
6	CO	
7	CO2	
8	Breakdown voltage	$\theta_j = -\infty, 1, 2$ (perfect condition: $-\infty$)
9	Water content	$\theta_{j,r} = 2$
10	Acidity	$R_{j,r} = 0.25$
11	Dielectric dissipation factor	$R_{j,m} = 0.25$
12	Interfacial tension	$r_{j,b} = 1$
13	Colour and appearance	$\theta_j = -\infty, 1, 2$ (perfect condition: $-\infty$)
14	Inhibitor content	$\theta_{j,r} = 2$
15	Corrosivity and passivator content	$R_{j,r} = 0.125$
		$R_{j,m} = 0.125$
		$r_{j,b} = 1$
16	DP-value	$\theta_j = DP = 0 - \infty$ (perfect condition: ∞)
		$\theta_{j,r} = 200$
		$R_{j,r} = 0.75$
		$R_{j,m} = 1$
		$r_{j,b} = 0.01$

*Not to be included for transformers where gas contamination from the tap changer is possible, as this is a common gas in tap changers

C. Statistics-based end-of-life model

This model is based on data from a scrapping database under development in Norway. The database includes measurements of DP-value at scrapping, as well as historic load, temperature and oil test data. Most of the transformers in the database were taken out preventively due to poor condition, but some were scrapped following a failure.

The scrapping data is used to establish a model for the transformer technical lifetime. Technical lifetime is here defined as the time interval from commission to failure occurs or until DP = 200 is reached. The technical lifetime for the scrapped transformers is hence estimated as follows: For transformers that were scrapped due to failure in the active part (2 transformers), the technical lifetime is set equal to the age at scrapping. For preventively scrapped transformers (14 transformers; mainly scrapped due to old age), technical lifetime is calculated as the age at scrapping plus estimated remaining life until DP = 200 is reached. The remaining lifetime calculation is done using the winding degradation model in section A with the DP-value measured at scrapping as input. For preventively scrapped transformers where the DP value at scrapping is not known (3 transformers), the age at scrapping is used as a lower limit for the technical lifetime, i.e. these data are viewed as right censored. The results from the analysis is shown in Fig. 2. All the transformers included in the analysis have standard Kraft insulation paper. As of today, there is not enough data to produce a similar analysis for transformers with thermally upgraded paper.

The fitted normal distribution in Fig. 2 can be taken as an approximation of a probability distribution for failure of the active part. This implies modelling the active part as non-repairable. Furthermore, this is a conservative approach, as the condition DP = 200 used in obtaining Fig. 2 does not necessarily cause failure, and the underlying population of scrapped transformers is likely representative of transformers of below-average condition.

To use the probability distribution in Fig. 2 further in this paper, the health indices of the scrapped transformers are also needed. Fig. 3 shows the health indices of the transformers as a function of calendar age, calculated with the health index model in section B. The health indices of the transformers before scrapping have also been included here. To obtain a common basis for all transformers, and since data availability today is limited, only the condition data that are available for most transformers have been included in Fig. 3, i.e. data $j = 1 - 10$ and $j = 12$ in TABLE I. It is expected that more of the data in TABLE I can be included in the future, as there is ongoing work to improve and increase the scrapping database, and as a newly established national database with oil test data also will improve data availability.

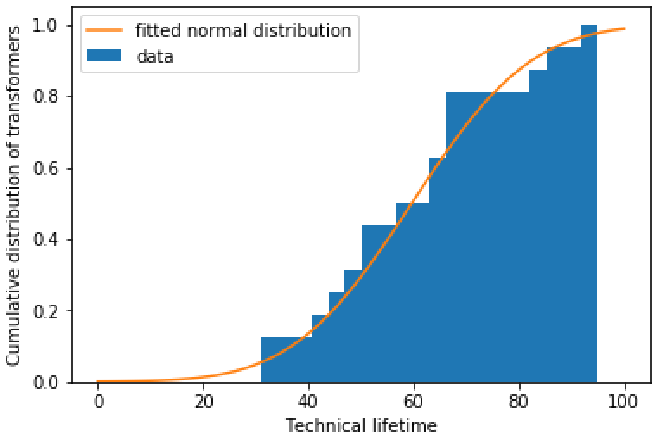

Fig. 2. Accumulated distribution for technical lifetime of a selection of transformers in Norway examined by SINTEF Energy Research, including a cumulative normal distribution fitted to the results (with mean and standard deviation 60 and 18, respectively). All transformers have standard Kraft paper

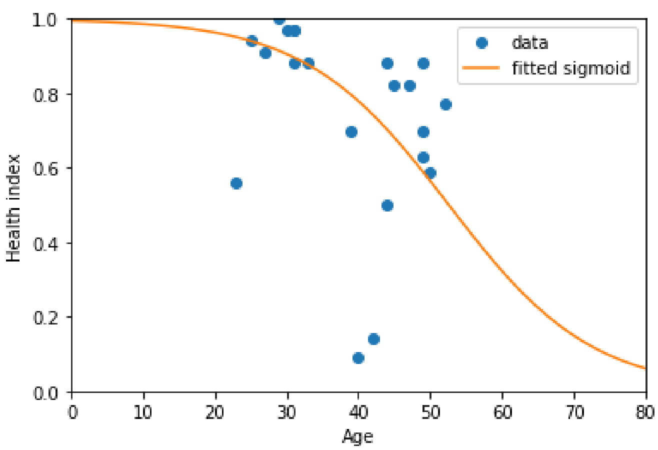

Fig. 3. Health indices for some scrapped transformers as a function of calendar age, including a sigmoid function fitted to the data

Since the health index is bound between 0 and 1 and should be monotonically decreasing, a sigmoid function is a logical representation for the data. The sigmoid function fitted to the data in Fig. 3 is given by:

$$HI(t) = \frac{1}{1 + e^{0.1t - 5.3}} \quad (8)$$

No correlation between health index and age is apparent in Fig. 3. In fact, a lot of variation in the data is as expected, since there is considerable variation in transformer designs and operation. However, when more data becomes available, it should become visible that HI approaches 1 as the age approaches 0 and 0 for very high ages.

It is clear from Fig. 2 and Fig. 3 that the number of transformers in the statistical basis is very low, due to the scrapping database still being under development in Norway. Hence, the results in Fig. 2 and Fig. 3 cannot be expected to be in general representative for transformers in Norway, but is likely representative of transformers of somewhat below-average condition for the active part.

IV. Risk Analysis and Lifetime Estimation

Risk is given by the probability of failure combined with the consequences of failure. There are many possible causes of failure for transformers. In this paper, only the active part of the transformer is included, and it is modeled as non-repairable. This means that the only type of failure that is included here is failure of the active part that results in full transformer breakdown resulting in replacement.

The statistics-based model makes it possible to estimate a condition-dependent risk for the transformer, i.e. to determine the transformer failure probability from its health index. This is done through the transformer's so-called apparent age. The apparent age is the age implied by its health index when it is compared to the health indices of the scrapped transformers. It is calculated by solving (8) for the time, with the transformer health index (scaled to match the number of condition data that Fig. 3 and (8) are based on) as input.

From the apparent age today, τ_{now}, the probability P_n that the transformer will fail within year n from now is estimated by

$$P_n = \frac{F(\tau(n)) - F(\tau(n-1))}{1 - F(\tau_{\text{now}})} \quad (9)$$

where $\tau(n)$ is the expected apparent age at the end of year n and F is the cumulative distribution function from Fig. 2. This equation assumes that the probability distribution in Fig. 2 can be used as an approximate failure probability distribution for any transformer, if the distribution is used as a function of the transformer's apparent age (i.e. its health) rather than as a function of its real age. Hence, (9) links the three basic models introduced in the previous section: F is given by the statistics-based end-of-life model, and takes the apparent age as input. The apparent age is given by the health index, in which winding degradation is included.

The future aging of the transformer is taken into account in (9) by assuming that the transformer ages as fast as its average

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aging rate in the past, i.e. that it is exposed to the same stress level in the future as in the past. Hence

$$\tau(n) = \tau_{\text{now}} + \frac{\tau_{\text{now}}}{t_{\text{now}}} n \tag{10}$$

where t_{now} is the current calendar age of the transformer.

Consequences of failure can for example be assessed in terms of economy, personal safety or environmental impact. This paper is limited to economic consequences. The cost of failure depends on the size, location, importance, etc. of the particular transformer, and includes costs for damages due to the failure, cost of energy not supplied or lost production, costs for purchase, installation and commissioning of a new transformer, cost for removal of the old transformer corrected for the residual value, etc. These costs are not detailed any further in this paper but must be assessed by the transformer owner.

From the failure probability, the expected time to failure or remaining life RL can be calculated as

$$RL = \sum_{n=1}^{\infty} (n - 1/2) \cdot P_n \tag{11}$$

V. Maintenance and Replacement Analysis

The estimated winding degradation, health index and failure probability together provide a good basis for assessing whether the transformer needs maintenance or replacement and when it should be done. A technical-economic cost-benefit model is proposed here, enabling a systematic way to carry out such assessments. The model mainly focuses on replacement, but also oil regeneration and reinhibitation are discussed. The latter two measures are only relevant when certain parameters of the oil are bad. Furthermore, in this model it is assumed that oil regeneration and reinhibitation will be followed by a replacement of the transformer when the effect (lifetime) of the measure is over. This assumption is included to enable a reasonable comparison between these two measures and replacement of the transformer. The model can be used to estimate the optimal timing of measures.

The benefit of maintenance and replacement is given in terms of the resulting improvement of the transformer condition. This reduces the probability of failure and may also give reduced operational and maintenance costs. In case of replacement, the new condition becomes as new. In case of oil regeneration, parameters $j = 10$ to 14 in TABLE I become as-new, while for reinhibitation only the inhibitor content ($j = 14$) becomes as-new. From this, the health index and thus the apparent age and failure probability after the maintenance or replacement is calculated using the models in the above sections.

Maintenance or replacement may also change the aging rate, as given by (10). For oil regeneration and reinhibitation, the aging rate is assumed not to change, as these are measures with a limited effect. After a replacement, the aging rate of the transformer is assumed equal to the real aging.

For measures not implemented today but planned to be implemented in a few years, the transformer condition at implementation is not known. This makes it difficult to predict the benefit of maintenance at this time. For regeneration and reinhibitation, the reduction of the apparent age is for simplicity assumed to be the same as if the measure was implemented today. Due to this simplification, the model should only be used for assessing postponing of measures a few years (e.g. up to 10 years).

The cost-benefit model calculates the present value of the net benefit of a measure, i.e. revenue minus costs, over a chosen number of years (e.g. 20 years). It is assumed that a measure will change the future costs, but not the future revenue, and therefore only costs are included in the analysis. The present value C_N of costs over an analysis period of N years including a measure that is being implemented in the year l is given by

$$\begin{aligned} C_N = \sum_{n=1}^{N} \frac{C_{om,n}}{(1+r)^n} + \sum_{n=1}^{N} P_n \frac{C_{f,n}}{(1+r)^n} \\ + \left(1 - \sum_{n=1}^{l-1} P_n\right) \frac{C_{m/r,l}}{(1+r)^{l-1}}, \end{aligned} \tag{12}$$

where the first term represents operational and maintenance costs $C_{om,n}$ in year n, the second term represents costs $C_{f,n}$ associated with a failure in year n, the third term represents costs $C_{m/r,l}$ associated with maintenance/replacement implemented in year l, and r is the discount rate. For generator step-up transformers in power plants the failure cost $C_{f,n}$ includes lost revenue due to lost production. Notice that in both the second and third terms in (12), costs are calculated for each year by spreading them equally throughout the lifetime of the transformer or measure, respectively, and then summing up over the analysis period. Also, these terms are adjusted for the annual probability of failure P_n given in the previous section. The profitability of a measure is finally calculated as the difference between the total costs in the analysis period with and without implementing the measure during the period.

VI. Example

The proposed method has been implemented in a transformer asset management tool for Norwegian utilities. The usefulness of the method is illustrated by applying it to selected transformers for one of these utilities. Note that this example is provided for illustration only, as some of the input data were of low quality.

The method has been tested on 18 substation transformers, listed with selected key data in TABLE II, including four transformers that were already preventively scrapped a few years ago. The results are shown in a risk plot for the transformers in Fig. 4. This illustrates that the model is well suited for comparing transformers in a population and for identifying high-risk transformers. In establishing Fig. 4, detailed cost data for the transformers could not be obtained. Therefore, a simple model has been utilized to obtain the cost of failure, for illustration purposes only. This model simply

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estimates the cost of failure as the cost of energy not supplied to consumers plus the cost of buying a new transformer. Both are estimated based on the transformer rated power and voltage, combined with some confidential historic cost data from the utility. Note that some of the transformers in Fig. 4 have thermally upgraded insulation paper, and that the presented results therefore likely are conservative for these.

TABLE II
LIST OF SUBSTATION TRANSFORMERS ANALYZED IN THE EXAMPLE, WITH SELECTED KEY DATA

No.	Rated power (MVA)	Cooling mode	Age	Paper type	Status
1	200	ONAF	11	Upgraded	In operation
2	200	OFAF	33	Upgraded	In operation
3	116	OFAF	58	Standard	Scrapped 2012
4	200	ONAF	8	Upgraded	In operation
5	167	OFAF	54	Standard	In operation
6	80	OFAF	58	Standard	Scrapped 2010
7	125	ONAN	49	Upgraded	Scrapped 2014
8	300	ONAF	13	Upgraded	In operation
9	300	ONAF	6	Standard	In operation
10	300	ONAF	6	Standard	In operation
11	250	OFAF	37	Upgraded	In operation
12	250	OFAF	38	Upgraded	In operation
13	160	OFAF	35	Standard	In operation
14	116	-	57	Standard	In operation
15	160	OFAF	50	Upgraded	In operation
16	200	OFAF	36	Upgraded	In operation
17	200	OFAF	45	Upgraded	In operation
18	107	OFAF	54	Standard	Scrapped 2011

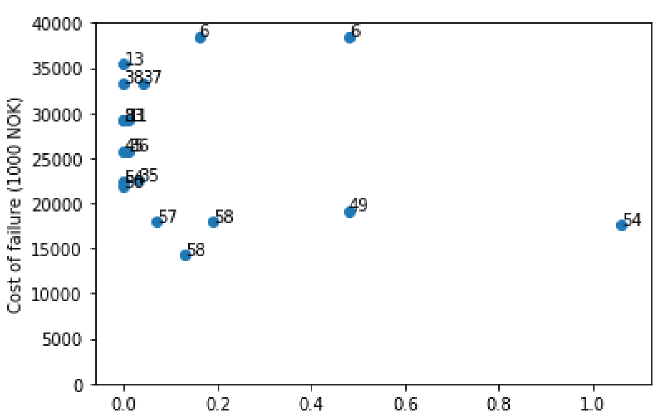

Fig. 4. Risk plot for selected transformers at a Norwegian utility. The markers are labelled with the transformer age

There are considerable individual variations in Fig. 4. These may be due to differences in design, loading, maintenance etc., as well as age. There does not seem to be a general trend with an increasing failure probability with the transformer age. This illustrates that evaluating transformers for replacement simply based on age is not a wise approach. The poor condition of the transformers is due to both gassing and deteriorating oil condition. For two of the transformers, also relatively low DP-values contribute. For the transformers that were already scrapped a few years ago, the illustrated results show the estimated risk if the transformers had still been kept in operation today. These transformers all place themselves to the right in the figure, indicating that they were relevant objects for scrapping consideration. Post-mortem investigations showed that two of these transformers had DP-values approaching 200 (i.e. 250 and 230) when they were scrapped, while the other two had somewhat higher DP-values (i.e. 354 and 523).

Results from a maintenance and replacement analysis for one of the transformers are shown in TABLE III. For this transformer, the expected time to failure or remaining life is estimated to 41 years. The model predicts that the most profitable course of action is to reinhibit the oil immediately, because this transformer had a low condition score for the inhibitor content. Replacing the transformer is not evaluated as profitable. Note however that this analysis is provided only for illustration, as actual cost data for the transformer was not available. It must also be remembered that the model does not take into account all positive effects of replacing the transformer. For example, reduced failure probabilities for other components than the active part are not taken into account, and consequences of e.g. fire or explosion have not been quantified as costs. Also, for substation transformers as analyzed here, rerouting via another transformer is often possible. The failure costs are expected to be higher for generator step-up transformers where failure can cause lost production.

TABLE III
MAINTENANCE AND REPLACEMENT ANALYSIS FOR TRANSFORMER 7 IN TABLE II, GIVING THE NET VALUE OF THE COST INCURRED DURING THE ANALYSIS PERIOD (20 YEARS) FOR RELEVANT IMPLEMENTED MEASURES. THE MEASURE EVALUATED AS MOST PROFITABLE IS BOLD FACED

Measure	Cost (1000 NOK)
No measure	1074
Regeneration, year 0	603
Regeneration, year 5	742
Regeneration, year 10	895
Oil reinhibitation, year 0	**330**
Oil reinhibitation, year 5	585
Oil reinhibitation, year 10	811
Replacement, year 0	12170
Replacement, year 5	8079
Replacement, year 10	5007

VII. DISCUSSION

A health index as proposed here is useful for ranking transformers, but it is important to clarify *what* type of ranking the health index is to be used for. The proposed method is designed to be used to support long-term transformer management, i.e. major maintenance measures and/or replacement, and *not* in day-to-day operations or short-term maintenance decisions. The proposed health index is first and foremost an index for prioritizing transformers for replacement. The absolute value of the health index should not be emphasized, rather it is the value of the index relative to the indices of other transformers that is of most interest.

The method does not attempt to identify what the underlying

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cause of a poor condition is. Before making final decisions for individual transformers, they should be analyzed in detail using additional investigations and/or measurements, as well as consultation with transformer experts.

The availability of data varies a lot, and for some transformers it may be rather poor. This is to some extent handled by the method. Specifically, in the winding degradation model, if load and temperature data are not available for the whole lifetime, the known load and temperature data series are assumed applicable throughout the lifetime. For the health index model, missing data are simply omitted, i.e. they do not contribute to a reduction of the health from the initial 100%. Of course, missing data does affect the thrustworthiness of the results. Although not described here, the method also includes a simple assessment of the quality of the input data, i.e. to which extent all the desired input data is provided.

It should be remembered that there is considerable uncertainty in the method. For example, the winding degradation model has large inherent uncertainties, including some conservative assumptions and simplifications. The grading and weighting of oil test data are necessarily somewhat subjective, although it is based on information from IEC standards. The method should therefore be further tested at utilities to gain more experience with it, and the weighting adjusted and benchmarked based on this testing.

The method is presented here for illustration, with the understanding that the data basis for it should be further improved. The statistical data that the method is based on is very limited as of today. With the current data basis, the method cannot be expected to be generally applicable for all transformers in Norway. Hence, improvement of the statistical basis is important further work. If the method is to be used in another country, a relevant statistical basis should be established for that country.

The method may be further developed. The condition model can be improved by utilizing national statistics for oil test parameters, in accordance with recommendations by IEC. There is not sufficient data available in Norway to do this today, but a national database with oil test data has newly been established and is being populated. Furthermore, this data may be useful for correlating condition data to failure modes, which can give a basis for improving the method to provide the health index based on an evaluation of failure modes, instead of directly from condition data. This will give a more physical basis for the health index.

The scope of the method can be increased by including also other components than the active part. The most interesting components to include are bushings and tap changers, since these have significant failure frequencies. However, this requires that gradable condition data are measured and registered also for these components.

The method in this paper does not differentiate between different types of transformers, except for the separation into standard and thermally upgraded insulation paper. This is due to the current small database of scrapped transformers on which the method is based. However, both construction, technology, geographic location (network / power station) as well as other factors can affect the condition and lifetime of transformers. The scrapping database under development and the newly established national oil test database will in the future provide a much better data basis for refining the method.

VIII. Conclusion

In conclusion, the presented method is a systematic approach to assess and rank the condition of power transformers. The method enables transformers to be compared, transformers requiring attention to be identified, and suggests the best course of action for maintenance or replacement. The calculated health index reflects the probability of major failure of the active part. However, these assessments are necessarily uncertain. Therefore, the transformers should not be assessed based on them only, but also on the underlying data, assumptions, models and uncertainties, as well as additional investigations as needed.

The proposed method utilizes data commonly available in Norway today. Application of the method on selected transformers from a Norwegian utility shows its usefulness in identifying transformers in poor condition, and for follow-up and prioritization of transformers for maintenance or replacement. This enables the total potential lifetime of a transformer fleet to be better utilized. The method should be further tested at more utilities. The trustworthiness of the model may be further investigated by benchmarking it with the help of transformer experts, and by post-mortem analysis of scrapped transformers that can be compared with method predictions.

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X. References

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