# Asset Management of Large Electric Machines through Monitoring of Electric Insulation

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*Abstract: Demanding requirements on the circular economy, cost savings, the effectiveness of the power grids operation press the operators of large electrical machines and other equipment to search for new methods of equipment management, maintenance, and renewal. At present, the management of important electrical machines is mostly related to offline concepts. This paper brings a summary of the current management practices and represents an introduction of a modern approach - Condition Based Management as well. For the large high voltage, electric machines are here proposed method of using aging models as a part of online diagnostic systems to estimate machine state. An example of the modeled use of condition-based modeling and residual life of insulating material is here presented. This approach should be employed in the employment of new renewable energy resources as well.*

*Keywords: asset management; residual life; insulating system; aging model*

# 1 Introduction

Historically, important high voltage electrical equipment such as transformers, generators, and cables, has been operated and maintained using so-called Time-Based Management (TBM). TBM has scheduled maintenance connected with diagnostics where the intervals of investigation are based on experience. These intervals can also be derived based on special requirements, e.g. by technical standards, etc. [29, 31, 32]. Of course since the modern electrical industry emerges, there have been ways to monitor or control some of the processes “online”. However, feedback control and monitoring of analog diagnostic signals cannot be considered as what is currently considered “Online Monitoring”. At present, operators need detailed information about current devices' status to optimize their use, use of overall resources, to make correct and economically efficient decisions. At the same time, it has to be stated that much electrical equipment is not maintained within the meaning of this article, it means without scheduled or online diagnostics, maintenance, etc. Often the action takes place after a failure when the failed unit is repaired or replaced by a new one, which is called– Incident-Based Management. This procedure is used, for example, because of insufficient infrastructure, lack of funds for prophylaxis, or, for example, because of relatively inexpensive replaceable components or whole units compared to the cost of diagnostic investigations or equipment for it and/or lack of knowledge or qualified personnel. Of course, this solution can be applied if the failure of the equipment does not have a direct impact on other important processes or if the risk is acceptable.

Asset Management is a term involving the general management of assets with maximum efficiency to generate added value. An asset is defined as a device generating economic profit. We then monitor the reliability of these assets. Asset management can be described as a recurring cycle of four activities: acquisition, operation, and maintenance, liquidation, and planning.

From the time point of view we can divide the asset management into short-term (mainly monitoring of the reliable operation), medium-term (maintenance, shutdowns), and long-term (strategic planning and liquidation).

From the diagnostic point of view, the most interesting is medium-term asset management, which mainly consists of maintenance and maintenance planning. The aim is to balance economic costs with some acceptable level of risk. Economic costs can be viewed from two angles. First of all, it is the cost of the maintenance intervention itself, including, for example, its design and preparation, etc. Furthermore, it is necessary to consider the costs associated with lost profit in the case that no substitution is available. The maintenance process is then planned for individual steps based on the recommendations of the manufacturers of the equipment (or according to special regulations) and the basis of the diagnosed equipment state. These diagnostic tests are performed when using TBM periodically with a given time interval. Due to the complexity of this issue and the variability of monitored objects, including the variability of their states, there are no simple schemes for general planning. Therefore, different sources of information (databases) are used, often unfortunately with different structures and without appropriate links. As a result, the monitored objects are diagnosed and therefore maintained at different intervals, which complicates the final decisions.

Long-term Asset Management deals mainly with strategic development and investment planning. Investments must be preceded by a thorough analysis, in which the options are examined in detail, together with a risk analysis [1, 2, 4].

Individual terms used in Asset Management:

- Incident-Based Maintenance (IBM) - there is no need for predictive diagnostics and therefore the cost of it, on the other hand, the length of repair and hence the shutdown cannot be planned,

- Time-Based Maintenance (TBM) - this system is usually used for important equipment, where off-line diagnostic procedures are developed, limit values of monitored parameters are normalized and reports on the status of monitored equipment are issued regularly with an outlook to the future status – e.g. estimation of remaining technical life, etc. The increase in reliability is measurable and can be verified. However, the staff evaluating diagnostic data must be experienced in the field and must be able to use various physical, empirical, and statistical procedures to determine individual results and propose follow-up actions,
- Condition Based Maintenance (CBM) - is a modern method mainly implemented in the power energy sector, e.g. in Canada and China.

  This method utilizes online monitoring of the equipment, especially its carefully selected parameters, which can be used to obtain information about the status of the equipment and to plan maintenance based on online data,
- Forecast Based Maintenance (FBM) – it is a system using CBM and aging models for planned interventions to increase the reliability of a whole,
- Reliability Centered Maintenance (RCM) - the main goal here is reliability,
- Risk-Based Maintenance (RBM) - the main goal here is safety,
- Proactive Maintenance (PRM) - The term is substantially equivalent to the following,

Sometimes following categories can be merged CBM, FBM, RCM, and RBM into one collectively called Condition Based Maintenance. To properly determine the state, it is necessary to diagnose it and to transfer online data, process it, and evaluate it in real-time.

Diagnostic signals and their limits must be established to implement any of the modern methods of asset management. Moreover, aging models (may be based on different principles), sensors, measuring equipment capable of operating reliably in all circumstances, monitoring of loads, and various external influences on the equipment together with secure transmission and storage of this data have to be available. The system must be able to process and evaluate the data in real-time. This result is then finally reviewed by specialists.

Through monitoring, for example, of the function of the cooling pumps and the oil temperatures before and after the cooler in case of liquid immersed power transformer, it can be stated surface contamination of heat exchanger remotely. Additionally, monitoring the increase of the composite value of dissolved gasses, it is possible to monitor the influence of the transformer load on the so-called “gassing” and thus to monitor the state of the insulation system. Also, by monitoring the water content in the oil, it is possible to observe either a thermalization disorder of the container or the gradual degradation of the cellulosic component of the electrical insulation system. Acidic hydrolysis of cellulose produces water molecules, which are then dissolved in the oil. Therefore, correctly interpreted information about the amount of dissolved water in the oil measured as a function of time can reveal the degradation state of the solid component of the electrical insulation system [18].

In terms of online measurement itself, in recent years, technical developments have enabled the emergence of online measurement systems capable to measure most of the necessary parameters, and at the same time, the infrastructure for the transmission of large volumes of data has been built. Industrial computers already have sufficient durability, reliability, and performance to process and send data, and at the same time, these “big data” [4, 15] can be stored in network storage. All this enables the rapid development of online diagnostic systems. This new approach should be incorporated also in the new energetic strategies of the EU which are being proposed and built recently [3].

The authors have proposed and working on a relatively cheap solution for variable use in the area of the diagnostics of electrical equipment. The new idea is to connect all in previous gained experiences and results and connect it to calculate the residual life of the machine. The concept lays in the proper description of the aging process of the weakest part of the observed machine. The description could be through the empirical, statistical, or physical model of the time degradation process in the weakest part. This process of degradation is online monitored through sensors and an onsite monitoring unit. This unit is not only sending measured data to some cloud as is now usual, but using the data to continuously calculate the „cumulative load“ of the weakest part using the introduced aging model. The process of the calculation finishes with the current state identification and is sent to the operator or the owner of the observed machinery.

The current situation is the measuring and storage of the data in the case of the large electric machinery a practical no data in case of smaller machinery (50-500 kVA) [32, 34, 35, 36].

## 1.1 Residual Life Modeling

One of the ways how to determine the current state of the monitored object/equipment is the use of aging models. These models can be of empirical, physical, or statistical nature and by their nature describe the time dependence of the monitored parameter up to the limit state. To use these models correctly, we need to know their parameters, which are either obtained experimentally by increasing degradation factor (accelerated tests) or from “experience” (e.g. statistical data) or based on the knowledge of the physical or chemical process taking place and leading to observed object gradual destruction.

When estimating a machine state, we must take care of model validity limits, and aging in machine operation must match the model. This means that if we have, for example, a model of the behavior of electrically insulating material under thermal stress and in practice this system ages mainly by temperature, then the estimation is accurate (assuming that the system accurately monitors the temperature). Conversely, if we have the same model and the electrical insulation system ages dominantly by another degradation factor (e.g. by the impact of the surrounding environment) the estimation will not correspond to reality. For this reason, research and testing are still carried out on various degradation factors and especially on their combinations (direct and indirect interaction, Figs. 3 and 4). A schematic diagram of the procedure for implementing the online EIS residual life calculation system is shown in Figure 11.

# 2 Aging Models

Using aging models to estimate the condition of the equipment is one possible access to this problem. The whole diagnostic system using these models then works on the principle of monitoring the identified important degradation parameter (temperature, number of starts, mechanical stress, operating hours, etc.) and implementing measured values into an aging model. The calculation then results in the “model state” of the monitored object/device. This model state more on less corresponds to the actual state of the monitored object. The advantage is that we can estimate the condition of the monitored devices concerning the actual operating load and thus the actual “consumed” service life can be estimated. An example could be three identical machines designed 15 years of operation. The first is loaded at rated power, the 2$^{nd}$ is cyclically overloaded and the 3$^{rd}$ is operating at minimum power. Let's say that the temperature was chosen as the most relevant degradation factor. The online diagnostic system estimates the lifetime already used (corresponding to the designated technical life) of the first machine, 13 years after 13 years of operation. The second overloaded machine, even if it has been in operation for 3 years only, will have an estimated consumed technical life of “14 years” (often operating at elevated temperature) and is, therefore, at the end of its technical life and needs to be replaced. On the other hand, even after 18 years in operation, the third lightly loaded machine has only consumed 80% of the estimated life (operating at low operating temperatures).

By employment of this process it’s possible to:

1) detect equipment that is approaching the end of its technical life (be prepared),
2) increase the reliability of a system operation,
3) reduce maintenance costs by targeting it to objects that need it,
4) reduce the costs by not decommissioning technically unused objects (otherwise they would be eliminated according to the schedule),
5) reduce environmental impact by optimizing the use of equipment,
6) enable central management of objects and thus increase the efficiency of a certain process.

## 2.1 Empirical Models

The main advantage of empirical aging models is the fact that we do not need to know the degradation mechanism in detail. We need to know the parameter that can be measured, and which corresponds to the degree of degradation. The endpoint criterion needs to be determined. The model is then sufficient to monitor the degradation impact of the selected parameter, and when the end criterion is reached, the appropriate maintenance/ replacement command is issued.

The power and exponential models are commonly used electrical aging models for monitoring, e.g. electrical insulating systems since EIS is usually the weakest part of the reliability chain in various high voltage equipment.

The power or inverse power model is one of the most commonly used models for the description of, e.g. electrical aging (1) [10].

$$\tau(E) = k \cdot E^{-N} \tag{1}$$

where $\tau$ is the estimated lifetime [h], $E$ is the intensity of the electric field [kV.mm$^{-1}$], and $k$ and $N$ are empirical constants.

The second most used is the exponential model, which is given by (2) [20].

$$\tau(E) = c \cdot e^{-kE} \tag{2}$$

where $k$ and $c$ are again empirical constants. The advantage of using such as simple model lays in the incorporation of the other aging mechanism, e.g. PDs (Partial Discharges) during electric aging with no need of understanding whole phenomena [16, 17].

Many processes can be described using empirical models, an example of a similar approach is the exponential model, based on the theory of the mechanism of crack growth at tensile stress according to Oding [20]. It is assumed that the vacant sites will move from the volume that is subject to elastic expansion to the less stretched ones. Calculates changes in vacancy concentration concerning crack formation due to tensile load.

$$V_{\mathrm{oc}} = \frac{dN}{d\tau} \tag{3}$$

$V_{oc}$ is the rate of coagulation and deposition of vacancies proportional to their number $N$ per unit of time $\tau$.

$$\tau = \left(\frac{C}{A}\right)^{\frac{1}{m}} e^{-\left(\frac{\alpha+\beta}{m}\right)\sigma} \tag{4}$$

where $\tau$ is the time to fracture ($h$),

$\sigma$ is the mechanical stress ($Pa$), *m* is an indicator characterizing the ability to accumulate vacancies,

*C*, *A*, $\beta$ are constants,

$\alpha$ is a parameter when, e.q. (4) is derived using Nadie model [20].

Equation (4) corresponds to the exponential relationship between load and fracture time. This equation is, therefore, equivalent to the equations for thermal (Arrhenius, Montsinger, Büssing) and electrical aging (2).

In previously mentioned models can be used for the description of the aging of any material that is exposed to the electric field. For empirical models, it is not necessary to know the degradation processes affecting the material. These models, however, fail when the aging mechanism is "far" from the condition during the test. This can be explained by the theory of a threshold intensity below which the electric field does not affect the aging of the material, see 2.4.

## 2.2 Physical Models

So-called "Physical" models refer to models that are based on the knowledge of the degradation process and thus reflect the actual processes in the object (not necessarily the physical nature). These models are potentially beneficial for the rapid development of technology because empirical models need to be parameterized by using accelerated aging, resulting in the usage of newly developed materials in the distant future. The disadvantage is in many cases limited knowledge of the degradation processes.

As an example, a double potential well/energy barrier aging model proposed by Crine [12], [13] is based on the theoretical assumption of the double potential barrier model, Fig. 1.

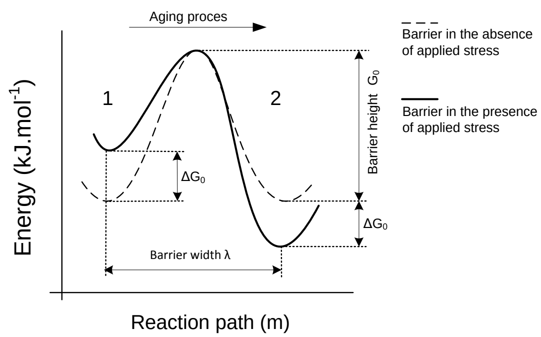


Figure 1

Double potential barrier used in the model presented in [6], [7]

$$\tau = \left(\frac{h}{k_B T}\right) e^{\frac{\Delta G}{k_B T}} \cosh\left(\frac{e_p \lambda E}{k_B T}\right) \tag{5}$$

where $h$ is Planck's constant,

$k_B$ is the Boltzman constant,

$\Delta G$ is the free activation energy,

$\lambda$ is the distance between the two states,

$e_p$ is the electrical charge of particles affecting the aging process. The parameters $\Delta G$ and $\lambda$ are temperature functions and are not precisely specified by Crine. This parameter represents the aging process and aging factor.

## 2.3 Statistical Models

Statistical models are based on “historical” operation data, e.g. measured failure rate. This access has several disadvantages, e.g. the data as a general rule do not contain information about the degradation process, the actual state of a particular object, the cause of the failure, etc. However, if there is a large number of the same objects, operated in the same way the statistical access is valuable.

Statistical and mathematical models based on statistical distributions create a good tool for the analysis of overall reliability. The distributions often used for calculation of reliability are, e.g. Weibull, Exponential, or Normal Distribution. The Weibull distribution is used in cases where the failure rate (FR) is not constant (Exponential distribution is employed where constant FR occurred). The Weibull distribution can be used for a description of the reliability of electrical devices in which the reliability of these systems and their subsystems depend on the number of operational hours, service age, or number of operational cycles. The probability density of the two-parameter Weibull distribution is given by equation (6).

$$f(t) = \frac{\beta}{\eta} \cdot \left(\frac{t}{\eta}\right)^{\beta-1} \cdot e^{-\left(\frac{t}{\eta}\right)^{\beta}}, \text{ for } t \geq 0 \tag{6}$$

where $\beta$ is the shape parameter and $\eta$ is the scale parameter.

The β parameter, shape parameter - affects the resulting distribution shape. If $\beta < 1$, then the instantaneous failure rate decreases, and if $\beta > 1$, then the instantaneous failure rate increases. A special case is $\beta = 1$, where the Weibull distribution is equivalent to the Exponential distribution and the instantaneous failure rate becomes constant. These limit values of the parameter β values are characteristic for the construction of the bathtub curve.

## 2.4 Physical-Statistical Models

Newly introduced models that combine all of the above. The physical or empirical model describes individual degradation mechanism (of which model is known) and inserted as a parameter of statistical distribution, e.g. three-parameter Weibull distribution, which allows to model different phenomena in all parts of the bathtub failure curve. The model TAMRT (TAMRT - Thermal Aging Model Respecting the Threshold) using this principle was published [12, 10] (7).

$$\tau(T) = A_1 \cdot \mathrm{e}^{\left[\frac{\mathrm{E_{a1}}}{\mathrm{R \cdot T}} \cdot A_2^{B(T)} \cdot e^{\left(B(T) \cdot \frac{E_{a2}}{R \cdot T}\right)}\right]} \tag{7}$$

where the constants $A_1$ and $A_2$ depend on the temperature, the properties of the system, and the number of particles; $T$ is the thermodynamic temperature [K]; $E_{a1}$ and $E_{a2}$ are the activation energies of thermal aging of the described EIS [J·mol$^{-1}$]; $R$ is the universal gas constant [J·K$^{-1}$·mol$^{-1}$], and $B$ (T) is the function defining the threshold value of the degradation factor $T_T$ [19]. A graphical interpretation is presented in Fig. 2.

This model was developed to describe and estimate a threshold $T_T$ of a degradation parameter, the temperature, in this case, a limit where a different aging mechanism appears. Above-mentioned models did not consider these limitations.

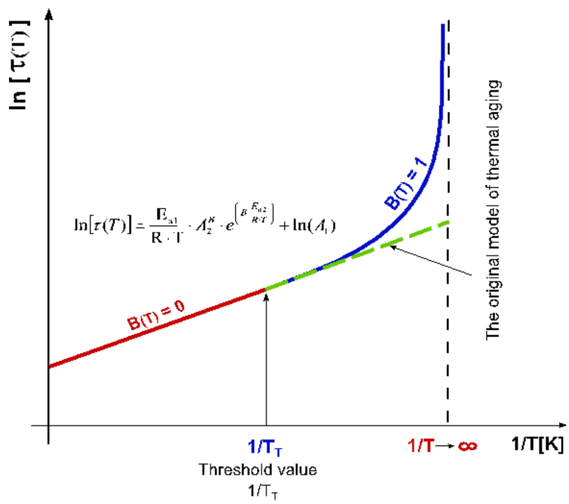


Figure 2

Thermal Aging Model Respecting the Threshold – threshold in the aging curve

## 2.5 Multifactor Models

Of course, when using online diagnostic monitoring, several degradation factors need to be monitored at the same time since they act often and at the same time, e.g. temperature, mechanical stress, moisture, electric field, pollutants, etc.

If we do have and employ several models, this means for each monitored degradation factor a special aging model in the Asset management system, thus we obtain several parallel results of the object state estimation. Therefore, there is an ongoing effort to identify interactions of degradation factors and merge their effects into one multifactor model. However, this is even more difficult than addressing the issue separately. The individual degradation factors interact and the result need not necessarily be the algebraic sum of these degradation effects. The literature distinguishes mainly two basic types of interactions - direct and indirect. The direct interaction, shown schematically in Fig. 3, is the simultaneous interaction of all degradation effects that interact with each other to such an extent that their action is significantly different from the condition if these factors act individually. An example of direct interaction is, for example, oxidation at elevated temperatures.

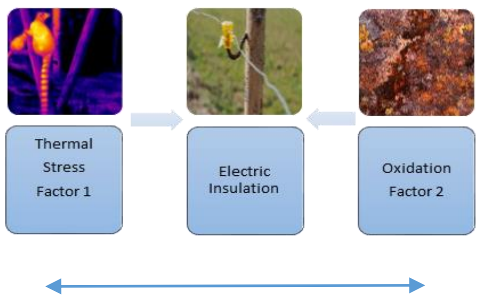


Figure 3
Direct interaction

Indirect interaction (Fig. 4) [20] is the simultaneous interaction of two or more degradation factors, the individual effects act in this case on the observed object separately. It is, therefore, a conditional influence on the parameters by degradation. An example of this interaction is the effect of electrical and mechanical stress. Mechanical stresses can cause cracks in the material, and in these inhomogeneities, partial discharges will occur, causing further material degradation.

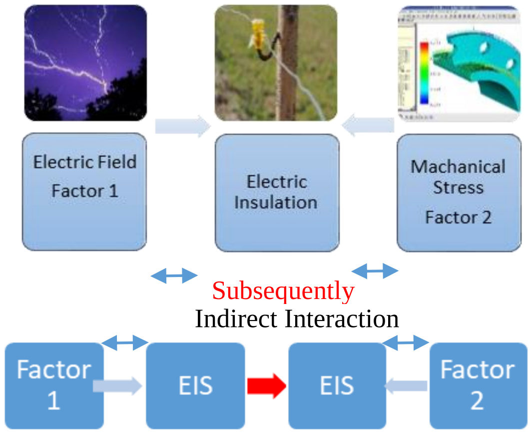


Figure 4
Indirect interaction

Above-mentioned interactions must be taken into account when constructing a multi-factor aging model. Conversely, an empirical model may include these factors without fully understanding their synergies.

# 3 Results and Contribution

## 3.1 Establishing of Life Model

An example of an aging test performed on slot insulation material used in high voltage rotary machines is presented in Fig. 5 and Table 1. The results are presented in the form of identified parameters of the exponential model. The three different stresses have been applied AC 50 Hz, high-frequency pulse voltage 6 kHz with a pulse width of 10 μs, and combined pulse and thermal. Individual points in Fig. 5 represent time to BDV of individual samples of insulation.

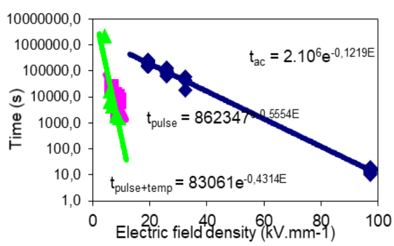


Figure 5
Electrical and combined aging curves of polyester slot insulation

Table 1
Identified parameters based on equation (2)

| Aging | Parameter *c* | Parameter *k* | Estimated Time to DBV for 3 kV/mm (h) |
|---|---|---|---|
| AC | 2.106 | 0,1219 | 385 |
| Pulse | 862347 | 0,5554 | 45 |
| Pulse + thermal | 83061 | 0,4314 | 6 |

This model is now usable for an introduced system of state estimation in the following text.

## 3.2 Online Monitoring and Life Calculation Example

The premise of an experiment: If an isolation system is exposed in operation to one permanently dominant degradation mechanism, other mechanisms can often be neglected, and only the most important one can be modeled. Samples of transformer board with dimensions of 100x100x1 mm were conditioned in laboratory conditions for 48 h and subsequently aged in hot air dryers equipped with a bushing for applying stress voltage. In this case, the electrical aging by increased value was applied to the samples up to the breakdown that occurred. The samples, Fig. 6 were placed between the circular electrodes. The number of samples at one voltage level was 6. The evaluation was performed by excluding outliers, determining confidence intervals at the required level of significance, and extrapolation for lower stress. The resulting regression model for this arrangement has the form:

$$R_{AF} = \frac{R_F}{22650.e^{-1,029.V}} \tag{8}$$

Where is $R_F$ resistance function of the insulation system *(h)*

$R_{AR}$ relative aging rate (-)

$V$ is applied voltage (V)

Figure 6
Samples of the transformerboard used for model evaluation

The Compact DAQ module from National Instruments was used for data acquisition. This system consists of a chassis and measuring modules. The cDAQ-9181 chassis, which has 1 slot for the measuring module, and the cDAQ-9184, with four slots, were used. Both chassis are equipped with an Ethernet output, which can be used to send the measured data over a local network, but also over the Internet. The NI9207 measuring module has a 24-bit converter, 8 voltage, and 8 current inputs and enables measurement with a frequency of 500 S / s. The module processes voltages in the range of ± 10 V and currents in the range of ± 21.5 mA. A four-channel NI 9211 module with 24 bit resolution and K-type thermocouples were used to measure the temperature. The measured values were stored in a TDMS (Technical Data Management Streaming) database. This data format is suitable for processing large volumes of data. TDMS files can also be opened in the MS Excel spreadsheet, so working with these files is comfortable for users. The measuring chain was composed of various sensors for the measurement of electrical and non-electrical quantities. The signal is further fed to the data acquisition device, either directly or via separating elements. Subsequently, the signal is processed depending on the nature of the quantity. These are mainly amplification, interference filtering, galvanic isolation, and digital signal conversion. The data acquisition device is connected by some type of bus to a computer, where the final signal processing takes place.

The evaluation unit repeats two cycles in an infinite loop - computational and display. The calculation cycle is used to read the input data and for the calculation itself. After the input signals are read, these values are read into the input buffers of the evaluation unit. This then calculates $R_{AR}$ and residual life $(R_F)$ according to a predetermined model, in this example (8). The calculated data is stored in the database and at the same time in the output buffer, which is user-configurable while the program is running. In addition to the current status, the user can also monitor an arbitrarily long interval of previous records. These are displayed in a table but also graphically. Both are automatically updated when the new value of the input parameter is read. The second cycle reads the measured and calculated values from the database, compiles a CSV file from them, and sends them to a remote server. This ensures the transfer of data to the central repository, but at the same time, it is possible to provide data in this way, for example, to external experts for follow-up analyzes. These two cycles can be solved using two independent programs, which is especially suitable if the execution frequencies of the two cycles are very different. However, it is necessary to handle the situation when both cycles need to work with the database at the same time. Because the measured parameters are only slowly variable, these cycles have been integrated into a single computational loop, eliminating the complication of dual access to the same database. The disadvantage of this solution is the suboptimal use of system resources. The validity of the above-mentioned methodology for determining the residual life, the functionality of the measuring chain, and the correctness of the subsequent processing were verified es well experimentally using simplified models of insulating elements. Models obtained in previous tests were used for verification. The same specimens were prepared for the construction of the aging model, and these specimens were placed in the same test space, where a variable AC voltage was applied to them. The voltage amplitude was increased and decreased at random time intervals, which was to simulate a variable material load in operation. It was necessary to choose the intensity of loading concerning the assembled aging models for the insulation system. Excessive load intensities would lead to skewed results due to different physical processes (or different degradation mechanisms). Too low load values would also affect the accuracy of the calculation, but especially in long-term monitoring. This is due to the exponential nature of the relative rate of aging. The relative aging rate and residual life were calculated from the measured stress by the prepared software tool. The values of applied stress, relative aging rate, and residual life were stored together with the time stamp in the TDMS database. This was then opened in an MS Excel spreadsheet and these data were plotted in graphs.

Fig. 7 shows the time courses of the applied alternating voltage and the corresponding relative aging rate for transformerboard samples. Fig. 8 calculates the relative aging rate and residual life.

The same graph shows the electric breakdowns of individual samples marked with numbers 1-5.

Fig. 8 is proof of the proposed concept since individual tested samples aged by the voltage variated in time, according to Fig. 7, came to breakdown (end of technical life) as expected ($R_F$ line Fig. 8 close to time = 0).

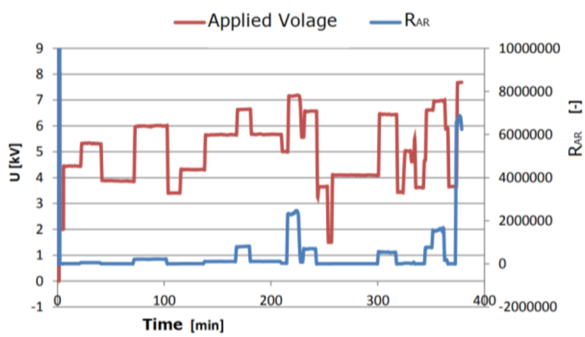


Figure 7

Time courses of the applied alternating voltage and the corresponding relative aging rate

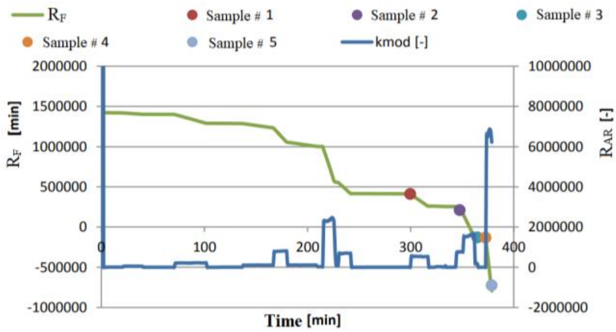


Figure 8
Online calculations of the relative aging rate and residual life estimation RF

## Discussion and Conclusions

Currently frequently discussed topics are Smart Grids, Industry 4.0, or recovery from Black Out from different points of view. A problem connecting these topics is the knowledge of the actual state of important elements of the whole of interest. Smart grids are power and communication networks that enable real-time regulation of power generation and consumption. Once implemented, power generation and consumption can be automated, which can be beneficial when deploying many decentralized sources. However, actual operating load/generation data must be in real-time available. This means including malfunctions and shutdowns, etc. of, e.g. distribution transformers. The use of decentralized resources can support but also worsen the stability of the network. Information network infrastructure for data communication has already been or is being created and can therefore also transmit device status data and online diagnostics data enabling calculations (model) that will lead to the forecast of the status of individual objects in such a network.

The impact of the introduction of modern methods of Asset Management of electrical equipment lays in the increase in the reliability of monitored equipment, reliable energy transmission planning, and maintenance and replacement planning. Other indirect impacts include reduced environmental load and feedback to the production and design process of important electrical equipment leading to their further improvement.

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