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Monitoring of End Winding Vibrations using Neural Networks

***Abstract**. In this paper the applicability of a radial basis neural network for monitoring of generator end winding vibrations is investigated. The modelling of the vibrational behaviour is needed to detect changes in the mechanical structure of the machine at an early stage. A case study and a significance analysis on operating parameters are presented. Furthermore the thermal equalization process after due to changes in operation is discussed.*

***Streszczenie.** W pracy zbadano możliwość zastosowania sieci neuronowej w monitoringu drgań połączeń czołowych uzwojeń generatora. Wczesne wykrycie zmian w strukturze mechanicznej maszyny jest możliwe dzięki modelowaniu drgań połączeń czołowych uzwojeń podczas pracy generatora. W pracy przedstawiono studium przypadku oraz analizę istotności parametrów pracy generatora. Przedyskutowano również wpływ procesów termicznych, zachodzących w generatorze pod wpływem zmiany parametrów pracy, na jakość modelowania siecią neuronową. (**Monitorowanie drgań połączeń czołowych uzwojeń z wykorzystaniem sieci neuronowej**).*

Keywords: end winding, monitoring, neural network, operating parameters, temperature, vibration.
Słowa kluczowe: połączenia czołowe, monitoring, sieci neuronowe, parametry pracy, temperatura, drgania.

Introduction

In the past few years the requirements in electrical power generation have changed and will change further in the future. Due to the enhanced volatile power generation with wind power plants and photovoltaic conventional power plants have to compensate sudden changes in the renewable power production. Because of the sudden and often changes in load the generators of conventional power plants and especially their end windings are stressed more, than through predictable changes. Furthermore disturbances in operation lead to a faster ageing of the end windings. To prevent a sudden damage of the generator or unplanned downtimes of the power plant it is important to monitor the condition of the end windings continuously. The use of an online monitoring system which focuses on the end winding vibration enables the inspection of the mechanical structure and its behaviour during operation. Tool to monitor critical end winding vibrations are presented [1]. This information is important to estimate the mechanical abrasion of the end winding insulation and the possibility of a short circuit which may destroy the whole generator. Of course the condition of the insulation not only depends on mechanical influences and has to be determined by separate measurements like partial discharge investigations, but the vibrational monitoring allows the detection of changes at an early stage and therefore makes possibly needful repair work schedulable.

In addition to the mechanical structure the vibrational behaviour depends on the operating conditions of the generator. To separate these two influences it is necessary to model the vibrational behaviour with respect to its significant operating parameters. The analytical or numerical modelling of power plant generator end windings is extremely difficult and expensive because of their complex structures and linked excitation relationships. In this way it is important to use a flexible method to predict the vibrational behaviour depending on the operation point of the generator as reference. In [2] a regression approach is used to model the vibrational behaviour of the end windings on basis of existing measurement results.

This paper focuses on the possibilities of neural networks in modelling the vibrational behaviour of end windings in operation to detect changes in the mechanical structure at an early state. In a first step the excitation mechanisms for end winding vibrations and their dependencies on significant operation parameters and the temperature are described. Afterwards the structure of a promising radial basis neural network and its utilization are shown. Finally an application example for the detection of a structural change in the end winding region is given.

End winding vibrations

End winding vibrations are excited due to several influences. First of all the stator core of the generator deforms in operation because of the magnetic forces resulting from the magnetic flux in the air gap. The bars of the end winding are wedged in the stator core so that the vibration propagates through the whole end winding. One other excitation mechanism results from the electromagnetic field in the end winding region and the current through the bars of the end winding. The electromagnetic field itself results from the current through the bars and the stray field at the end of the stator core. Both excitations rotate synchronously but have an angular offset and different amplitudes which depend on the currents I1, I2, I3 and IF in the generator or the operation parameters active power P and reactive power Q. Furthermore there may be coupled vibrations of other machine parts like shaft vibrations, which propagate over the bearings, the casing and the stator core to the end windings. The propagation from other machines over the fundament is possible, too.

Beside the different excitations the mechanical structure of the end winding has a big influence on the resulting end winding vibrations.

There are other significant operating parameters near the active and reactive power. If the electrical machine is driven by different rotational frequencies this parameter is from most significance. As the stiffness of the end winding structure depends on its temperature and the natural frequencies depend on the stiffness it is logical that the significance of the bar temperature profile may be very significant in cases where the exciting frequency is near to a natural frequency.

The measurement of end winding vibrations has high requirements because of the high electromagnetic fields in the end winding region and the high voltage potential of the bars. The use of sensors on a fiber-optic principle allows the undisturbed measurement of accelerations which can be integrated to vibrational signals. These signals can be analyzed by a Fourier transform which results in a harmonic representation of the signal. Because of the excitation mechanisms there are only a few significant harmonics for the vibration of a tight end winding bar. Other harmonics occur especially when the bar gets loose so that different bars may hit each other.

Neural modelling of end winding

In the following a neural network for the monitoring of end winding vibrations is used. The method can be applied to single bar vibrations with focus on local loosening or damage, as well as to overall modal vibrations resulting from a modal analysis [3].

The following considerations are discussed in the context of a single bar vibration.

For the determination of mechanical system changes within the end winding the complex relationships between vibration and operating parameters have to be taken into account. The modelling of the vibration based on neural networks is a good method, in which a neural network is trained with vibration data and operating parameters of an intact end winding.

The neural network is supplied with process variables and simultaneously measured vibration values. With this information, the network begins to learn the actual condition of the machine. In this training the network adapts to sets of input and output vectors until the total error between predicted and actual vibration is sufficiently low. It should be noted that as the entire relevant operating range has to be covered by the training data. Then the vibration behaviour can be simulated using the network with new operating parameter sets as input. The difference between simulation and real measured vibration data now provides a measure of the change in the vibration behaviour of the machine. If the deviation is too large, the mechanical properties of the end winding or of the generator have changed.

For the modelling of a neural network for deviation detections radial basis functions (RBF) are suitable [4]. In the following the harmonic parts of a vibration are treated separately. One harmonic has a sinusoidal time dependence of its state variables. The vibrations of an individual winding bar consists usually of vibration components of first and second speed harmonic, which can be extracted by a Fast Fourier transform of the entire vibration signal and processed by separate neural networks.

RBF networks consist of two layers with different tasks. The first layer consists of RBF neurons that detect the awareness of an input vector p compared to a weight vector w. The neurons of the second layer form thereof a linear weighted combination. An RBF neuron is activated in response to the distance between the input vector p and the weight vector w with a scaling factor b. The transfer function of the neuron is $radbas(n) = e^{-n^2}$. The more the input and weight vectors coincide, the nearer the output of the transfer function is getting to the value '1'.

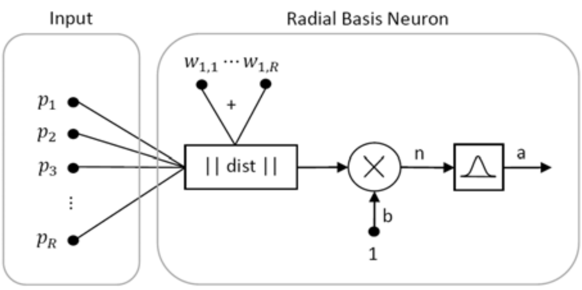

Fig.1. Schematic representation of a radial basis neuron

A RBF network is mainly used for function approximation. Continuous functions can be represented on a compact input interval with high precision, where each RBF neuron is responsible for a local region of the input interval. Therefore, a global approximation is performed by a variety of local approximations. Learning a new training pattern requires only a local adaptation of the network.

For the parameterization of the network the number of neurons has to be chosen properly. Too many neurons may lead to precise fitting the training data including unavoidable signal disturbances. Therefore, a suitable number of neurons compared to the training data should be chosen (e.g. factor 0.1). If the number of neurons, however, is set too low, the relationship between input and output vectors cannot be represented properly. For the present example, the use of 50 neurons per harmonic is sufficient, wherein the magnitude and phase of the harmonics are modeled separately.

The spread of the transfer function can be adjusted by the scaling factor b. The larger b is chosen, the smoother the function approximation. If the spread is too large, many neurons are needed to build a function with many course changes. In the case of a too small spread, however, many neurons are needed to build a function with a uniform course. The appropriate range must therefore be manually adjusted for each problem.

Significance analysis of operating parameters

The influence of the operating parameters on the vibration of the end winding can be determined by a significance analysis. Furthermore it can be worked out whether all essential variables are taken into account. In the present application, the regarded operating parameters are speed, active power, reactive power and field current. The significance of the operating parameters on individual vibration harmonics allows a differentiated approach.

To determine the significance, the vibration behaviour is learned for a given period, in which it must be ensured that all relevant operating parameters vary with time. If a simple neural network model is able to represent all vibrations correctly, all relevant information is contained in the measured data.

The significance analysis can be divided into two steps. In the first step, a small neural network, which is not suitable for an accurate description of condition, is trained with all available input variables over a fixed predetermined period of time. If even this network is sufficiently able to approximate the vibration behaviour accurately, all significant process variables are taken into account. In the second step, the significance of the individual operating parameters P_x with $x=1..n$ can be determined. For this purpose, it is examined how good the vibration characteristics can be mapped on the basis of a single operating parameter over a small neural network. As a measure of this the approximation error and the mean square distance A_x between the actually measured and simulated vibration characteristics can be used. As reference the approximation error A_0 is elected which occurs for a input without information (zero vector as input). The significance $S_{x,y}$ of an operating parameter x on a vibration variable y is in the value range of 0 to 1 and can be represented by the following formula:

$$S_{x,y} = \frac{A_{0,y} - A_{x,y}}{A_{0,y}} \tag{1}$$

In Fig. 2, the significances of the operating parameters second harmonic of an end winding vibration is displayed in form of a bar chart. From this it follows that the operating parameters of the active and reactive power have a significant influence. Rotational speed and excitation current, however, can hardly have an effect on the vibration behaviour seen.

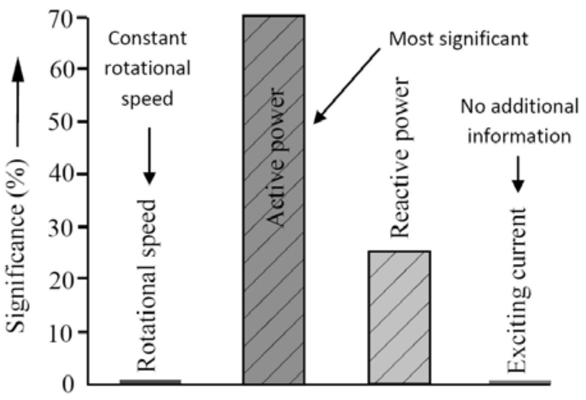

Fig.2. Schematic representation of a radial basis neuron

The overall significance of 95% indicates that not all essential operating parameters are taken into account. The thermal transition as a result of a load change, for example, was not included in the considerations. This would require a time delayed feedback loop within the neural network.

Neural vibration monitoring

Based on a trained neural network a change in the vibration behaviour can be detected with defined limits. For this, the differences of harmonic pointer variables can be considered. By using properly sized neural networks, the complex interaction of several parameters and their effects can be measured and predicted. Mispredictions can occur if the machine is operated with combinations of the process variables, which are not included in the primary training or the measured operating parameters are outside of a valid range, such as active power close to 0 MW. In this case, a secondary training of the network is required to expand the knowledge base.

Fig. 3 illustrates an exemplary time course of a vibration (gray) and an associated prediction (black) with magnitude and phase separated. For meaningful results, both variables must be taken into account. In addition the limits are shown, which are used in conventional surveillance systems to allow the detection of large deviations in the vibrational behaviour. In the example shown, there is an unrecognized short-term deviation of the real vibration characteristics for prognosis and a limit is exceeded. While the limit violation can be detected directly, the deviation remains undetected in the vibrational behaviour without a suitable vibration model.

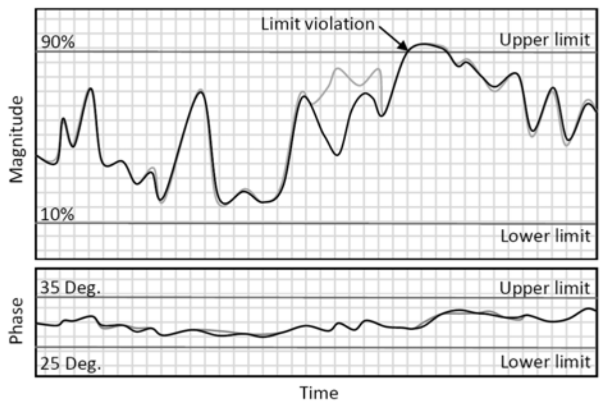

Fig.3. Schematic time course of prediction and measurement

Fig. 4 illustrates the difference between the signals in Fig. 3. This difference is referred to as the residual which allows an easy detection of behaviour deviations.

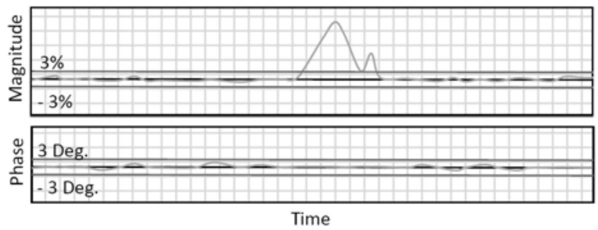

Fig.4. Residuals between prediction and measurement

The described method is now applied to a 300 MVA generator, which has been in operation for about 14 years. At the front of the end winding on the connection side five sensors are placed. These sensors recorded the radial vibration of the end winding over several years.

The evaluation of the records shows that only the vibration component of the second harmonic (2n) provides a substantially vibration. In addition to the vibrations also the operating variables rotational speed, active power, reactive power and excitation current were recorded. In this section the results of the neural simulation using a RBF network are presented.

The vibration data exist as vibration pointer with magnitude r_0 and phase φ for all five measurements. The values of each pointer will be processed separately by two neural networks of the same structure. The operating parameters rotational speed *DZ*, active power *P*, reactive power *Q* and excitation current I_E form the input vector for the neural networks. The absolute difference between measured and simulated vibration pointer represents a useful measure for assessing a vibrational change, whereas neglecting the phase information can be misleading.

Fig. 5 to Fig. 12 show the behaviour of the 2n-harmonic component of a winding bar on the connection end (CE) of the investigated turbine generator and associated operating parameters over a period of approximately one year. The rotational speed of all shown data is 2990-3010 rpm. Due to operation interruptions and measuring disturbances the number of records displayed is limited to about 1300.

The active power illustrated in Fig. 5 has the most significance. During the investigated period there can be two key active power ranges of 15% to 30% and from 50% to 85% identified. The training data must be chosen so that both active power ranges are included. As training data 400 time samples were selected with corresponding data sets. The selected training data are highlighted in the pictures.

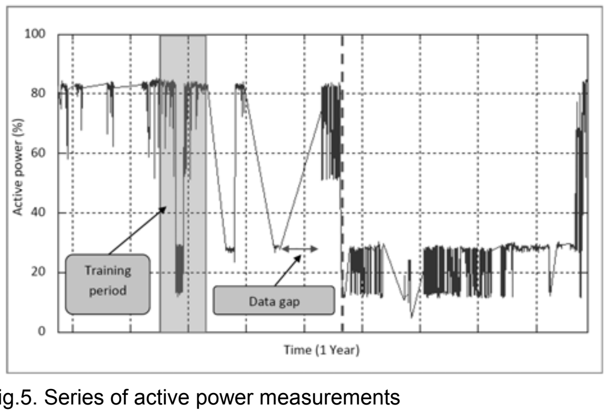

Fig.5. Series of active power measurements

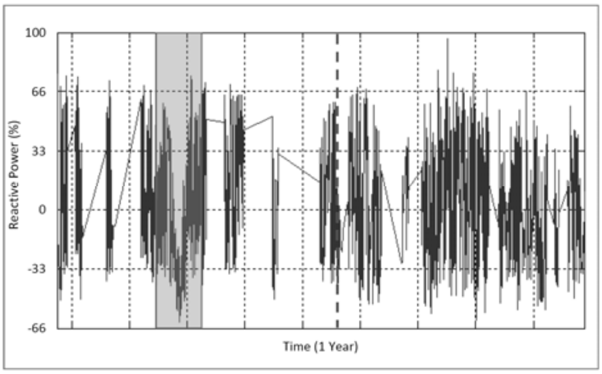

Fig.6. Series of reactive power measurements

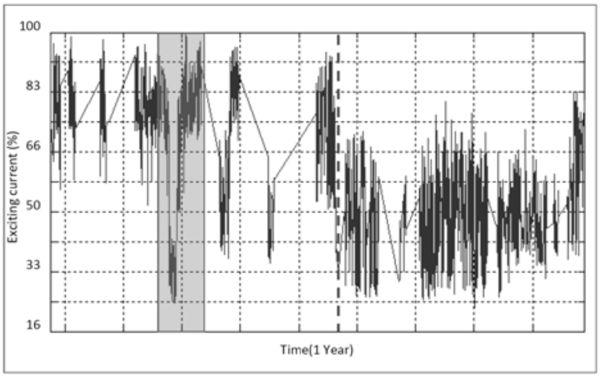

Fig.7. Series of excitation current measurements

Fig. 8 shows the measured vibration magnitude of a bar winding bar on the connection end (black), the training sequence used (highlighted) and the simulated vibration response (grey).

It can be seen that measurement and simulation are almost identical immediately before and after the training sequence. After some time, however, a large deviation between measurement and simulation occurs. This observation can be explained by a single pole ground fault (dashed line).

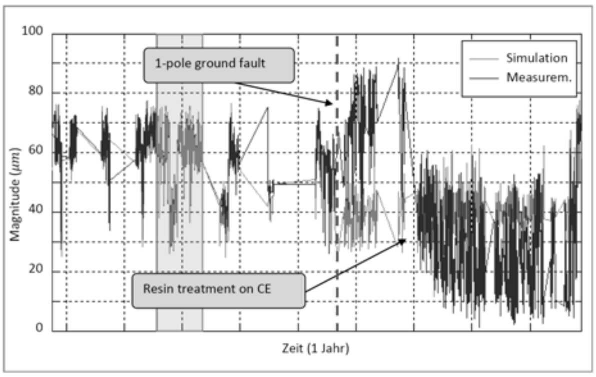

Fig.8. Measured and simulated magnitude of 2n-single bar vibration

During a subsequent inspection several damaged consoles were found on the connection end. In addition to the repair of the consoles the connection end was treated with resin.

Because of the visual findings the described vibrational change indicates a defect of the end winding. The vibration level was reduced after repair, but the original condition could not be achieved again.

Fig. 9 represents the deviation between the magnitude of measurement and simulation.

Two major but time-limited deviations can be seen in the period before the grid fault. This is due to a sudden change in operation which causes a relatively slow transition to a new thermal state of the generator. A change in the magnitude due to the grid fault is clearly visible. The corresponding oscillation phase is shown in Fig. 10. It can be seen that the grid fault caused no significant change in the phase of the observed vibration but the repair had a big influence. This can be seen from the phase deviation shown in Fig. 11 as well.

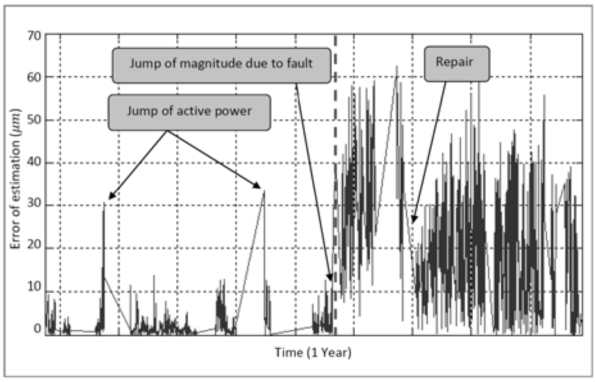

Fig.9. Magnitude deviation between simulation and measurement (see Fig. 9)

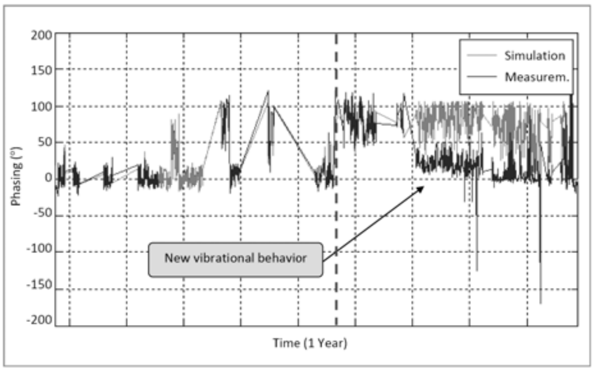

Fig.10. Measured and simulated phase of the 2n-single bar vibration

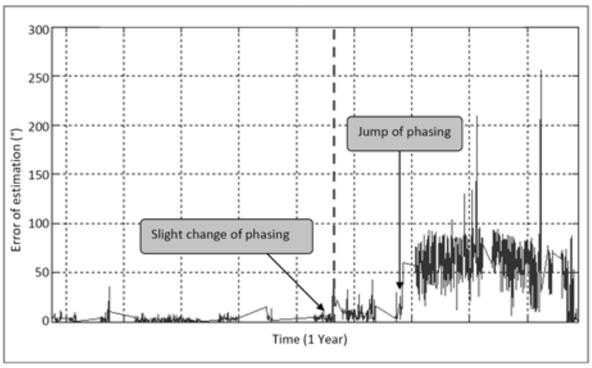

Fig.11. Phase deviation between simulation and measurement (see Fig. 10)

Fig. 12 represents the absolute pointer deviation between measurement and simulation. Herein the change in the vibrational behaviour is seen best, however, the previous pictures are also helpful for a differentiated evaluation of magnitude and phase.

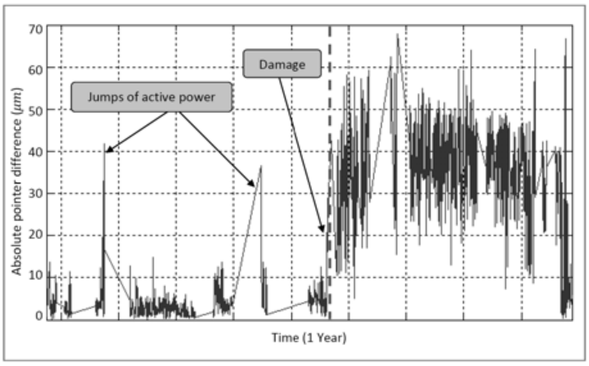

Fig.12. Pointer deviation between simulation and measurement of 2n-single bar vibration

Thermal equalization process

In the following a short trend of the absolute pointer difference is investigated (see Fig. 13). The training sequence extends over the entire area shown. In the time period being investigated incidents are not known. In addition a change in the vibrational behaviour can be neglected, since only two days are considered. The corresponding active power (see Fig. 14) and the reactive power (see Fig. 15) are shown as well.

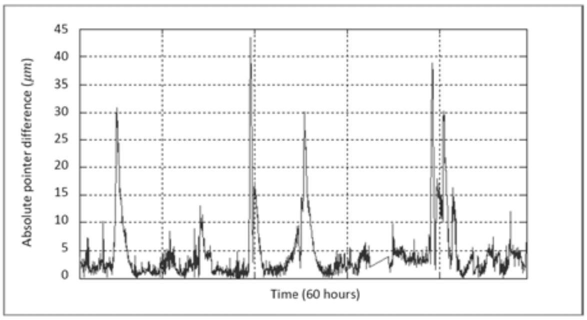

Fig.13. Absolute pointer difference between simulation and measurement

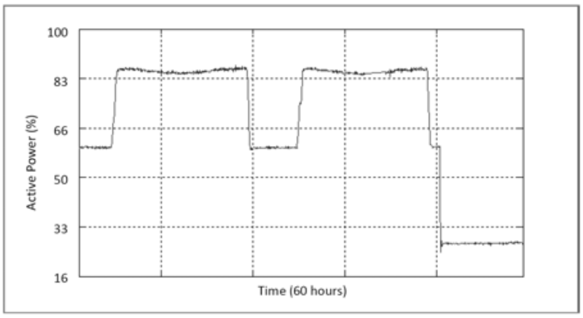

Fig.14. Measured active power

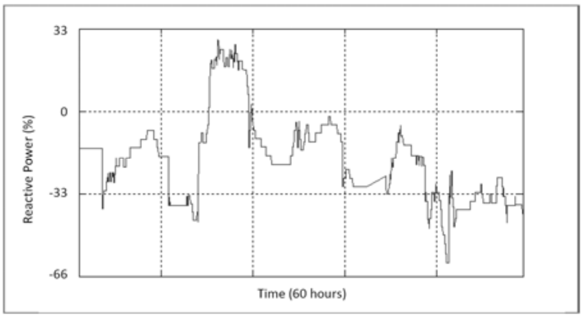

Fig.15. Measured reactive power

In the course of active power jumps are observed, of which each causes a thermal equalization process. The induced change in the vibration behaviour of the end winding will take up to two hours and appears to be related to the temperature adaption. The presented method cannot account for this change in temperature, since usually the temperature in the end winding is not recorded.

The investigated neural network only adapts to the stationary machine behaviour. This results in a deviation in the vibration prediction after a jump of active power. A thermal compensation process due to a significant change in active power for the considered machine takes about two hours.

From Fig. 13 and Fig. 15 it can be seen that the reactive power has an influence on the quality of vibrational prediction as well.

Conclusion

This paper illustrates the good results for modelling the vibrational behaviour of generator end windings with radial basis neural networks. A comparison of the simulated vibrations on basis of measured operating parameters with vibrational measurement result allows the detection of structural changes at an early stage. This gives the operator the opportunity to schedule repair and maintenance works and therefore to operate the generator more economic. The identified significant operating parameters are active power, reactive power and temperature for the operation of the investigated turbine generator.

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