Thermoelastic steam turbine rotor control based on neural network

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Abstract. Considered here are Nonlinear Auto-Regressive neural networks with eXogenous inputs (NARX) as a mathematical model of a steam turbine rotor for controlling steam turbine stress on-line. In order to obtain neural networks that locate critical stress and temperature points in the steam turbine during transient states, an FE rotor model was built. This model was used to train the neural networks on the basis of steam turbine transient operating data. The training included nonlinearity related to steam turbine expansion, heat exchange and rotor material properties during transients. Simultaneous neural networks are algorithms which can be implemented on PLC controllers. This allows for the application neural networks to control steam turbine stress in industrial power plants.

1. Introduction
Thermal stress control of steam turbines has been presented by Busse [1], Dawson [2], Pahl et al. [3]. All of these stress control systems used thermo-physical start-up probes, which were physical models of the steam turbine rotor. The thermo-physical start-up probe measures two temperatures: that of the steam turbine rotor and the mean rotor temperature. More accurate stress control can be achieved by using mathematical models of steam turbine components. Lausterer [4], Lausterer et al. [5], Ehrsam [6] have presented systems in which the mean temperatures of particular turbine components were calculated using a mathematical model and a start-up probe. Sindelar at al. [7] describe a system which assesses stress in a critical turbine component by using only standard power plant measurements. Rusin et al. [8] have presented a steam turbine stress control system based on Duhamel’s integral.

This paper for the first time presents a steam turbine stress control system based on a neural network used for the hot start-up and shut down. While neural networks have already been used in power system diagnostics, e.g. by Gluch et al. [9] [10] for diagnostics of power object geometry deterioration, never before have they been used for temperature and stress modeling in on-line steam turbine control systems. The neural networks presented in this paper are able
Figure 1. NARX neural network based steam turbine thermal stress control.

to simulate on-line the temperature and stress of a critical turbine component based only on standard power plant measurements, such as speed, power, steam temperature and pressure in front of turbine control valves.

2. Rotor strength modelling with neural network

NARX neural network stress control was implemented on the HP rotor of a 18K390 steam turbine.

2.1. Identification of critical points in a rotor

NARX neural network thermal stress control does not focus on the entire HP rotor, but only on its critical thermal stress points. In order to identify these points, a rotor lifetime assessment (LTA) was performed. This showed that there is only one critical point in the region of the first HP rotor groove.

2.2. Rotor stress control concept using NARX neural

Fig. 1 shows a diagram of the NARX neural network thermal stress control system. Different sets of measurements in the turbine are used in the control system for each period of the steam turbine lifetime.

In our research, seven turbine load cycle regimes were used. In each of these the steam temperature, steam pressure, turbine speed and turbine load were measured. These physical parameters are sufficient to describe rotor boundary conditions during turbine load cycles. Therefore these measurements were chosen as exogenous inputs to neural networks to identify critical point temperature and stress. The neural network steam turbine control system shows actual rotor temperature and stress in the critical point. The control system consists of three NARX neural networks (Fig. 1). The first of these assess critical point temperature during turbine standstill on the basis of the rotor’s axial expansion (absolute expansion AE, differential expansion DE, axial bearing float BT). This temperature is used as an initial temperature for the second NARX neural network, which assesses critical point temperature on the basis of turbine speed \( n \), turbine load \( N \), steam temperature \( T \) and pressure \( p \) before the turbine control valve during turbine start-up. Assuming that rotor is stress free at the beginning of turbine startup, the data concerning critical point temperature, turbine speed, turbine load, steam temperature and pressure before the turbine control valve allows the third NARX network to assess critical point stress.
3. FEM based neural network training

Neural network training is a process which allows to select network weights and biases in order to reflect known output data based on corresponding inputs. Here the neural network training was performed using the Levenberg-Marquardt algorithm, which was possible because of the series-parallel architecture. However, for the NARX neural network the most important factor is the training data.

In order to build a training data set which covers all possible variations of every inputs, 168 FE calculations for transient turbine rotor states were performed. The variation range of each neural network training data set was established on the basis of turbine operational history.

The only experimental possibility of verify the assumed heat exchange and FE models was through expansion of the rotor. Fig. 2 compares the FE analysis with measurements of axial expansion during a cold start up of the turbine. The dotted lines show the expansion, taking into account measurement errors. The results obtained from the numerical calculations and experiments are very close.

4. Neural network testing using experimental data

The HP rotor neural network control system was verified using experimental data. This included each turbine start up category (cold, warm I, warm II, hot), one sliding pressure shut down and one load rejection together with turbine reloading. As a measure of neural network performance, the root mean squared error (RMSE) was used. The maximal RMSE for neural network determined temperature was 5.4 °C and occurred during warm start up I. The other temperatures were: 5.39 °C for load rejection together with turbine reloading, 4.8 °C for cold start up, 4.2 °C for hot start, 4.1 °C for sliding pressure shut down and 2.1 °C for warm start up II.

The maximal RMSE for neural network determined stress was 18.8 MPa and occurred during cold start up. The other stress values were: 10.2 MPa, 11.3 MPa, 13.2 MPa, 8 MPa and 6.4 MPa. Fig. 3 presents the neural network determined temperature (Tm) and stress (Sig), including relatively errors, in the HP rotor critical location during hot start up. Fig. 3e and 3f show good FE-NET correlation for hot start up. Higher error values were observed in NET determined stress (Fig. 3f). This was because while temperature was determined only on the basis of exogenous inputs and feedback values, stress was not only based on exogenous inputs and feedback values but also on temperatures determined by the other network. Therefore errors in the temperature network affected the stress network (Fig. 3g). Fig. 4 presents neural network determining temperature (Tm) and stress (Sig), with errors, in HP rotor critical location for shut down. Fig. 4e, and 4f show that neural network results for shut down were close to finite element analysis. The relative error for temperature (Fig. 4g) is very small and for stress it is
5. Conclusion
A HP steam turbine stress control system based on a NARX neural network has been presented. The HP rotor neural network control system was verified using experimental data. Neural networks are able to simulate on-line, the temperature and stress of a critical turbine component based only on standard power plant measurements, such as speed, power, steam temperature and pressure in front of turbine control valves. This is a very promising system for controlling various transient thermal stresses of steam turbine and gas turbine rotors. This system can also be applied to control stress in many other power plant components, e.g. boilers, inner and outer casings etc., where it is difficult or impossible to make direct stress measurements on-line. Another advantage of this system are its low hardware requirements, which allow it to be implemented in existing controllers. Temperature and stress analyses show that obtained results from neural networks are very similar to results obtained using the finite element method. The results presented here are for only one critical point (the first groove of an HP rotor), but, after due training, it could be applied in many other points.
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