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Research Paper

Using the artificial neural network to control the steam turbine heating process

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HIGHLIGHTS

- Inverse Artificial Neural Network has a potential to control the start-up process of a steam turbine.
- Two serial neural networks made it possible to model the rotor stress based of steam parameters.
- An ANN with feedback enables transient stress modelling with good accuracy.

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ABSTRACT

Due to the significant share of renewable energy sources (RES) – wind farms in particular – in the power sector of many countries, power generation systems become sensitive to variable weather conditions. Under unfavourable changes in weather, ensuring required energy supplies involves hasty start-ups of conventional steam power units whose operation should be characterized by higher and higher flexibility. Controlling the process of power engineering machinery operation requires fast predictive models that will make it possible to analyse many parallel scenarios and select the most favourable one. This approach is employed by the algorithm for the inverse neural network control presented in this paper. Based on the current thermal state of the turbine casing, the algorithm controls the steam temperature at the turbine inlet to keep both the start-up rate and the safety of the machine at the allowable level. The method used herein is based on two artificial neural networks (ANN) working in series.

1. Introduction

Monitoring the stress state in power machinery components is an important aspect of supervising their safety. The knowledge of the stress state at any moment of operation makes it possible to assess the hazard posed by on-going processes, such as fatigue and creep, as well as the brittle cracking hazard. Therefore, the safety of operation requires determination of stresses in real time to allow an immediate response on part of the control system to the operating situation that arises [11]. This is of special importance considering the increasing share of RES-based power in national energy generation systems. In many countries wind farms have a considerable share in electricity generation. The problem is that obtaining energy from wind is a highly unpredictable process, and a sudden change in weather conditions may result in a power shortage in the system. In order to compensate for these shortages, a rather fast start-up of a conventional power unit is required. This, however, may have an unfavourable impact on the durability and reliability of the power unit elements, steam turbines in the first place. Therefore, conventional power units have to be characterized by very high, unprecedented flexibility, which means the capacity for frequent start-ups and shutdowns as well as for operation under variable thermal loads.

In recent years, the application of the Artificial Neural Network (ANN) algorithm has been more and more common in cases that require an immediate assessment of diagnostic signals. The ANN metamodel is a universal approximator of the function of several variables and constitutes a nonlinear model of a given process making it possible to obtain a response to set input parameters [7,8].

The problem of monitoring the gas turbine set operation is discussed in Fast's PhD dissertation [3], which shows the use of the ANN as a diagnostic tool. The neural network task was to classify diagnostic signals for the purposes of the gas turbine technical state assessment. At the same time, Fast and Palme published an article [4] showing the possibility of using the ANN to evaluate the operating conditions of a gas-steam combined heat & power plant. Each of the thermal cycle main elements (the heat recovery

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steam generator, the steam boiler, the gas turbine and the steam turbine) was modelled using a separate neural network. The networks were then combined into a single monitoring system. The diagnostics of the gas turbine failures was analysed by the authors of [10] using what is referred to as the *extreme learning machine*, which in fact is a neural network variant with a single hidden layer. The tool suitability was evaluated based on experimental data obtained for the gas turbine set gear under controlled conditions. Similar applications are presented by the authors of [5]. This time, however, in relation to the steam turbine operation safety and reliability. In this case, the neural network is used to assess the durability of the rotor blades. An interesting thing here is the inversion of the ANN algorithm to obtain desired input parameters for set output values. Thus, for a set level of durability, a certain value of the vibratory stress is determined which then constitutes one of 6 input data values. The presented calculations prove that the algorithm actually operates and it does so with high accuracy. The same computational technique was used in [2]. This time, to assess and determine the optimum operating parameters of a compressor. Based on a few measured thermodynamic parameters and setting the required level of the compressor efficiency, the necessary drop in the air temperature in the cooler was looked for. Such an application of the ANN is an example of the possibility of using it to control a given process.

Other applications of artificial intelligence are presented in the paper written by Huang et al. [6], where the network is used to model the temperature inside an airport building based on the weather data and parameters of the building air-conditioning system operation. Moreover, the system was extended to predict the temperature using weather forecasts, the number of passengers and the time of the heating-cooling system operation or standby. Several variants of the number of historical data supplying the neural network were also tested in the study. The precision of the authors' anticipations is at the level of 85–90%. The authors of [14] used the ANN to model selected operating parameters of a hybrid ground exchanger in a heat pump system. Based on the measurement of a few temperatures in different points of the cycle, the temperature of the medium flowing into the exchanger was predicted. Another example of the ANN application can be found in [1]. This time, in relation to the electric power system. Using a neural network, the authors establish the safety of the electric power system for different variants of the system operation and determine the need to take specific action. A neural network developed in this manner is a tool that assists the making of operating decisions.

This work shows an attempt to use the ANN to control the steam turbine operation. The problem, however, is the complexity of such a task. In reality, several parameters without a strong direct correlation have to be taken into account. Therefore, this paper shows a possibility of controlling the steam turbine start-up process by changing the steam temperature at the turbine inlet, keeping the thermal stress at an allowable level at the same time. Since the thermal stress depends on the element temperature and the computations are made for the turbine rotor, the rotor temperature has to be assessed based on possible measurements. The idea is to solve the problem by using two ANN's, where one is responsible for the temperature evaluation and the other – for the maximum stress control. The reason for which the approach based on two separate ANN's is adopted results from the initial need for the rotor temperature evaluation (as the quantity cannot be measured) based on the casing temperature, and not on the modelled thermal stress.

2. The principle of the ANN operation

The ANN operation is based on mimicking the human brain functions and the ANN component elements are artificial neurons that represent nerve cells whose task is to process input signals into output ones by means of simple mathematical operations. The network is composed of neurons arranged in layers and linked to each other to ensure the input-output flow of information [8].

A diagram of a typical neural network with a unidirectional information flow from the input to the output layer is presented in Fig. 1.

Each neuron in layer "i" is linked to all neurons of the neighbouring layer, transmitting the signal from the $(i-1)$ layer to the $(i+1)$ layer by means of what is referred to as the activation function. Because the input signals for a given neuron come from all neurons of the previous layer and because in fact their excitation strength varies, the signals in the ANN are burdened with weights whose task is to control the level of the signal reaching the neuron. A difference in the signal level has an effect on the neuron different activation and, consequently, on the signals transmitted further on.

3. The model of thermal stress determination

Modelling stresses in components of the power engineering equipment and machinery is usually realized with Finite Element Method (FEM). However, such simulations to directly monitor the operating conditions and to control the start-up processes involves acting in real time. In other words, the supervision system has to provide rapid answers to questions concerning for example the maximum stress values at current parameters of the power unit operation. For this reason, the input parameters of the stress determination metamodel must be measuring quantities that have a direct impact on the strength state of the elements under analysis. In the case of the turbine internal casing, the factors deciding about the stress state are the casing current temperature field (thermal gradients) and the value of the steam pressure in the flow system. For the rotor, apart from its thermal state – also the rotational speed value, which decides about the level of mass loads. Because the rotor material temperature is not measured in the industrial practice (due to the character of the rotor operation), a decision was made to model the rotor stress state based on characteristic temperatures of the casing material. Consequently, appropriate measuring quantities were selected: the casing metal temperatures in selected areas and the steam pressure in the turbine inlet chamber; for the rotor, additionally, the rotational speed. In real systems such measurements are usually possible. The metal temperature was measured at deliberately selected points where the difference in temperature during the start-up process corresponded well to the curve illustrating changes in the maximum stress values in the element. In the case of the HP part internal casing the areas are shown in Fig. 2.

One of these points (A) is the joint of the steam inlet connector pipe and the casing inlet chamber, which is located in the area of maximum unsteady-state stresses. The point is situated on the casing inner surface. Due to the very intense heat exchange in this area (very high heat transfer coefficients, heating on both sides of the joint), the measurement of the casing metal temperature is almost equivalent to the temperature measurement performed inside the turbine inlet chamber.

The other metal temperature measuring point (B) is located in the front sealing area on the same radius as point A, shifted however by 200 mm in the axial direction. This means that it is distanced by about 100 mm from the nearest heating surface – the surface of the steam spiral inlet chamber.

Determination of the rotor maximum stress values based on the casing temperature measurements presented above proved unsatisfactory. This was probably the effect of the lack of an unequivocal correlation between maximum stresses in the rotor and changes in temperature in the indicated points of the casing. Therefore, a