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Prediction in Regulating the Heat Treatment of Ferroconcrete

E. N. Chumachenko and A. M. Zak
Moscow State Institute of Electronics and Mathematics (Technical University)
e-mail: mmkaf@miem.edu.ru

Abstract—Neural networks are applied to the long-term prediction of parameter variation. Regulation of the heat treatment of ferroconcrete is considered as an example. Experimental results are presented. An algorithm is proposed for planning the operation of the executive mechanism.

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Ferroconcrete production in Russia is characterized by low thermal efficiency. For example, in Moscow, the most developed region, energy resources account for 10–50% of the total production costs. In that context, automatic control of the heat treatment of ferroconcrete is of interest. The production of ferroconcrete includes preparation of the concrete mixture; its transportation; shaping; heat treatment; and striking. Before it can be moved to the point of use, the shaped ferroconcrete must acquire the required strength. Hardening is the most prolonged operation. In normal conditions, concrete acquires 70–80% of its strength in 7–15 days and its full strength in 28 days [1]. The most effective means of accelerating this process is heat treatment [2, 3].We consider heat treatment by saturated steam (steaming), in which the parts are held in special chambers filled with saturated steam or steam–air mixture until the specified strength has been attained. The optimal temperature for accelerated hardening is 60–80°C; the moisture content of the steam is 100%.

The goal of the control system is to maintain specified temperature T_{sp} within the chamber. Typically, the temperature is specified for four stages: (1) preliminary holding; (2) heating; (3) steaming at constant temperature (isothermal heating); (4) cooling.

The heat treatment of concrete is a very energy-intensive process. The production efficiency and the product cost depend directly on the rational use of energy resources.

Strength is one of the most important characteristics of ferroconcrete. The strength is acquired during heat treatment. More precise maintenance of the thermal conditions and mixture composition ensures more rapid attainment of the required strength.

In the present work, we develop an optimal control system for heat treatment, which employs predictions of the target parameter. The regulator, which transforms the observed discrepancy into a control signal, is based on fuzzy logic. The predictions are generated on the basis of artificial neural networks, which are widely recognized as a universal tool in control, data filtration, shape recognition, time-sequence prediction, and elsewhere. The problem considered here is equivalent to the prediction of time sequences.

There is an extensive literature on prediction by neural networks. For example, short-term prediction of the power consumption at an industrial enterprise was considered in [4]. Daily predictions of the power consumption were obtained three days in advance, by means of recurrent Elman networks. Modified Elman networks were used to predict the power consumption in [5]. A generalized-regression neural network (GRNN) was used for weather prediction in Moscow in 1998 and prediction of phone-system breakdowns for 2002, in [6]. Multilayer neural networks were used to predict groundwater levels in [7].

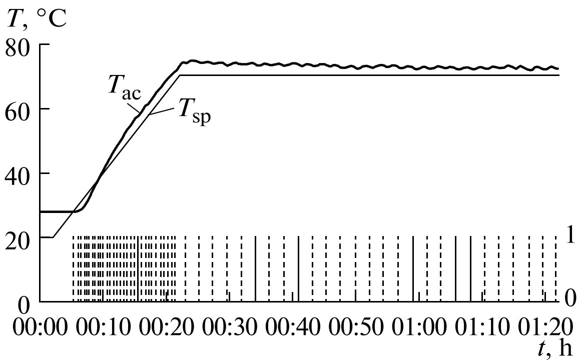
PREDICTION METHOD

Special laboratory equipment is built to test the temperature predictions generated by the prediction and control algorithms.

Short-term temperature predictions require the following data: the current temperature; the ambient temperature; the current state of the heater; and information regarding the past state of the heater.

Correspondingly, the neural network may have three-layer perceptron architecture [8, 9]. The inputs are the current temperature; the ambient temperature; the current state of the executive mechanism (the steam-valve aperture) and several previous states; and the pressure in the steam line. This data set is assumed sufficient for prediction of future temperature variation. Thus, the output layer corresponds to prediction of the temperature after some time interval.

This approach is tested in practice by means of laboratory equipment including a water-filled tank with an electrical heater; instruments connected to the computer for measuring the water temperature and the



Results of temperature regulation. The vertical lines denote the state of the heater: 1, heater on; 0, heater off.

ambient temperature; and equipment for controlling the heater. The neural network is a three-layer perceptron, with 20 inputs for historic states of the heater and one input for the current temperature; the intermediate layer consists of three neurons. The output is a prediction of the water temperature in 5 s. In fact, the output must be regarded as the current temperature shifted to the left on the time axis by 5 s. At this stage, the ambient temperature is disregarded. As a result of a training stage, we obtain a neural network capable of correctly predicting the water temperature in 5 s during the transition from stable cooling to stable heating and also in periods of stable cooling.

Now consider long-term prediction. As in short-term prediction, we employ laboratory equipment including a water-filled tank with an electrical heater; instruments connected to the computer for measuring the water temperature and the ambient temperature; and equipment for controlling the heater.

There is one more input than in short-term prediction: the temperature history over some period of time. The input layer of the neural network includes 20 values of the heater history and 21 values indicating the history of temperature variation. Only two heater states are possible: on (1) and off (0). The temperature history is a set of temperature values at 5-s intervals. The network's output consists of values of the water temperature in 5 s (short-term prediction). Long - term prediction involves repeatedly feeding the output back into the network.

The accuracy of long-term prediction is greatest for the following network configurations: 41–20–1; 41–40–10–1; 41–41–15–1. (The figures are the numbers of neurons in each layer.) The accuracy is 7–10°C at water temperatures of 20–100°C for the first two networks and up to 5°C at water temperatures of 35–100°C for the last network. In the experiment, we obtain networks capable of progressively more precise predictions, but within narrower temperature ranges.

We now consider a control algorithm for the heating system in accordance with the predictions obtained and the specifications imposed.

To prepare training and test data sets for the neural network, we employ data obtained on the laboratory equipment with the most typical transient states of the temperature, such as continuous heating to temperatures less than 100°C; a series of relatively long periods in which the heater is on; a series of relatively short periods in which the heater is on; and specified limits on the temperature in the laboratory equipment (continuous heating of the liquid from the ambient temperature to the boiling point).

The training and test data sets contain subsets (windows), each of which contains a complete set of initial values for the neural network, as well as the required output.

The training algorithm employed is the Rprop (resilient propagation) gradient method, on account of its fast convergence with respect to the classic back-propagation method (Backprop algorithm) [10, 11]. In contrast to the Backprop algorithm, the Rprop algorithm only uses the signs of the partial derivatives to adjust the weighting factors. The Rprop algorithm employs time-span training, in which the weights are corrected after the network has processed all the examples in the training set.

For each weight ω_{ij} determining the relation between neuron i and neuron j, we introduce a unique value Δ_{ij}, which uniquely determines the correction of the weight. In the course of training, Δ_{ij} conforms to the following rules:

$$\Delta_{ij}^{(t)} = \begin{cases} \eta^{+}\Delta_{ij}^{(t)}, & \text{if } \dfrac{\partial E^{(t-1)}}{\partial \omega_{ij}}\dfrac{\partial E(t)}{\partial \omega_{ij}} > 0; \\[2ex] \eta^{-}\Delta_{ij}^{(t)}, & \text{if } \dfrac{\partial E^{(t-1)}}{\partial \omega_{ij}}\dfrac{\partial E(t)}{\partial \omega_{ij}} < 0; \\[2ex] \Delta_{ij}^{(t-1)}, & \text{ot herwise,} \end{cases}$$

where $0 < \eta^{-} < 1 < \eta^{+}$.

The adjustment of the weighting factors proceeds as follows. If the partial derivative with respect to the weight ω_{ij} changes sign in step $t-1$, we conclude that the last change in the weight was too large, and the algorithm overshot the local minimum. In that case, Δ_{ij} is reduced by η_{ij}^{-} for step t. However, if the derivative retains the same sign, Δ_{ij} is increased in step t, so as to hasten convergence. When the corrections for all the weights have been found, we use the following rule to change the weighting factor: if the derivative is positive, the weight is reduced by Δ_{ij}; and, if the derivative is negative, the weight is increased by Δ_{ij}. In symbolic form

$$\Delta\omega_{ij}^{(t)} = \begin{cases} -\Delta_{ij}^{(t)}, \text{ if } \dfrac{\partial E^{(t)}}{\partial \omega_{ij}} > 0; \\ +\Delta_{ij}^{(t)}, \text{ if } \dfrac{\partial E^{(t)}}{\partial \omega_{ij}} < 0 \Rightarrow \omega_{ij}^{(t+1)} = \omega_{ij}^{(t)} + \Delta\omega_{ij}^{(t)}; \\ 0, \text{ ot herwise.} \end{cases}$$

If the partial derivative with respect to the weight ω_{ij} changes sign in step t—that is, if the algorithm overshot the local minimum in step $t-1$—we reverse the sign of Δ_{ij}

$$\Delta\omega_{ij}^{(t)} = -\Delta\omega_{ij}^{(t-1)}, \text{ if } \frac{\partial E^{(t-1)}}{\partial \omega_{ij}} \frac{\partial E^{(t)}}{\partial \omega_{ij}} < 0.$$

As a result of back propagation, the derivative changes sign again in the next step. To prevent repeated correction of Δ_{ij}, we must assume that $\partial E^{(t-1)}/\partial\omega_{ij} = 0$.

Once we have a correct long-term prediction of the target parameter, we may plan the optimal control signal. The algorithm's output should be a sequence of operations in which the heater is turned on and off, so as to maintain the water temperature in the laboratory equipment within the range $\lfloor T_{sp} - 5°\mathrm{C}, T_{sp} + 5°\mathrm{C} \rfloor$. In other words, the temperature specification should be satisfied. (As a rule, $T_{sp} = 50$–$80°\mathrm{C}$.)

The temperature specification is known, and the temperature history is sufficient for generating the initial set of input data. The time interval covered by the temperature specification is divided into 5-s segments, for the convenience of the network. Thus, this segment (increment) defines the minimum time of heater operation.

We now introduce the concept of a dead zone, so as to rule out extremely frequency switching of the heater. The dead zone is below the specified temperature: $T_{dz} \in [T_{sp} - \Delta T, T_{sp}]$ $(0 < \Delta T < T_{sp})$.

The prediction algorithm is as follows.

(1) Generation of predictions over the whole period covered by the temperature specification.

(2) Comparison of the temperature prediction T_{pr} in step 1 with the specified temperature T_{sp} for each specified point i. If $T_{pr} < T_{sp}$, the heater is switched on for the interval $[T_i - 5 \text{ s}, T_i]$, where T_i is the temperature is the temperature at the point being considered. If that restores the planned temperature, proceed to step 3; if not, continue step 2.

(3) Adjustment of the prediction over the whole interval of temperature specification, followed by return to step 2.

Obviously, the main deficiency of this algorithm is that the amount by which the temperature exceeds the specification is not monitored. At the present stage, however, this is not required.

After generating a sequence of control signals, it is reproduced in the laboratory equipment. Heater control does not include temperature feedback; we employ blind regulation.

TEST RESULTS

In temperature regulation for the laboratory equipment, we rely on temperature specifications with different temperature rise in the initial stage. As we see in the figure, the results show that, at the stage of temperature increase, the difference between T_{sp} and T_{ac} is no more than 5°C on average. (The error is around 7%.) The expected increase in T_{sp} is observed in the transient sections (within the limits of error). For specifications with prolonged maintenance of constant temperature, gradual temperature decline is observed.

Analysis of the results provides some information regarding the process [12, 13].

The error in predicting the discrepancy between T_{sp} and T_{ac} in each iteration may be considerably reduced by reducing the time increment. The discrepancy observed between T_{ac} and T_{sp} may be attributed to the failure to take account of the ambient temperature in training; in fact, the ambient temperature fluctuates from 19 to 25°C. Compensation of this error entails taking account of the ambient temperature in training or introducing an initial adjustment in constructing the prediction.

An undoubted benefit of the proposed control system is that the number of times that the executive mechanism is turned on is monitored. The system operate may make informed decisions in balancing the control precision and the life of the equipment. This permits long-term planning of the repair and replacement schedule for the equipment components.

In comparison with classical control systems, the proposed system is not greatly destabilized by the failure of temperature sensors. The system may operate autonomously for a long time, without corrections on the basis of up-to-date temperature data, while retaining the required precision. By contrast, instrument failure incapacitates classical control systems based on a PID regulator or a fuzzy regulator.

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