PASTEURIZATION MACHINE NEUROCONTROLLER

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The neurocontroller of the pasteurization machine was developed. It consists of two parts: the neuroemulator and the serial neurocontroller, which are based on the multilayer perceptron structure. The neurocontroller has been implemented as a module in the SCADA-system at OJSC «Savushkin product» and has a good effect in comparison with the conventional PID controller. Testing showed the effectiveness and fast response.

Key words: neural networks, neurocontroller, process control, pasteurization machine.

BASICS

Process control has become an integral part of process plants. An automatic controller must be able to facilitate the plant operation over a wide range of operating conditions. The proportional-integral (PI) or proportional-integral-derivative (PID) controllers are commonly used in many industrial control systems. These controllers are tuned with different tuning techniques to deliver satisfactory plant performance.

However, specific control problems associated with the plant operations severely limit the performance of conventional controllers. The increasing complexity of plant operations together with tougher environmental regulations, rigorous safety codes and rapidly changing economic situations demand the need for more sophisticated process controllers.

MODEL PREDICTIVE CONTROL

Model predictive control (MPC) is an important branch of automatic control theory. MPC refers to a class of control algorithms in which a process model is used to predict and optimize the process performance. MPC has been widely applied in industry. The idea of MPC is to calculate a control function for the future time in order to force the controlled system response to reach the reference value. Therefore, the future reference values are to be known and the system behavior must be predictable by an appropriate model. The controller determines a manipulated variable profile that optimizes some open-loop performance objective over a finite horizon extending from the current time into the future. This manipulated variable profile is implemented until a plant measurement becomes available. Feedback is incorporated by using the measurement to update the optimization problem for the next time step.

NEURAL CONTROL

The main differences in many MPC algorithms are the types models used to represent the plant dynamics and the cost function to be minimized. Obtaining such models is very complex task. What is more, any changes of external conditions involve model corrections, what is difficult too.

Control algorithm should be quite simple for understanding and implementation, has learning ability, flexibility, robustness and be nonlinear. So, neural networks are very good candidate for this position.

There are many approaches in neural control. According to [2] we can define:

• Serial control scheme. Neural network is learned to map desired signals into control signals.

• Parallel control scheme. Neural network is learned to compensate signals from conventional controllers (like PID).

• Self-tuning control scheme. Neural network tunes parameters of conventional controllers to bring closer output to desired signal.

• Scheme with an emulator and controller (back propagation in time). Some utility measure or time efficiency is maximized.

• Adaptive-critical scheme. This is a kind of the dynamic programming.

There is increasing interest in application neural technologies in the industry now. Let's have a closely look at the most effective and perspective approaches.

Serial control scheme. This is the simplest scheme, what is main advantage (can solve wide variety of tasks) and disadvantage (require retraining in case of change controlled object parameters) at the same time.

Learning algorithm is described further.

Back propagation in time scheme. «Back propagation in time» – one of the major neurocontrol architecture, which uses back propagation learning algorithm. Two neural networks are used in this scheme.

The first net is used as emulator, the second – as controller. Emulator can be learned off-line using general control architecture or directly by random input signals.

Emulator is learned in this way: suppose that in the time moment $t+1$ in the memory we have the current output $y(t+1)$, $q+n$ previous values of the same process and $p+n$ values of input process u (so, p and q defines the window size for input and output signals, n – the quantity of learning samples).

Learning sample for neural network (neuroemulator) we can define as matrix, which rows are characterizing input vectors for net. Let we get $y(10)$ why $y(11)$ isn't known yet and $p=3, q=3, n=3$. Also we have in the memory $y(9), y(8),...y(5)$ and $u(9), u(8),...u(5)$.

We get:

$$X = \begin{bmatrix} y(7) & y(6) & y(5) & u(7) & u(6) & u(5) \\ y(8) & y(7) & y(6) & u(8) & u(7) & u(6) \\ y(9) & y(8) & y(7) & u(9) & u(8) & u(7) \end{bmatrix}.$$

Sample for learning will be values $y(8), y(9), y(10)$ accordingly. That is the emulator prognoses output from previous input and output values. The emulator is been learning to get desired accuracy or maximum iterations count.

This approach can be used for on-line learning. If we have saved work data about the system we can use it for off-line learning as well.

Similarly to the emulator we can implement the neurocontroller using direct inverse learning. Sample will be values *u(8), u(9), u(10).* That is the neurocontroller prognoses control signal from previous input and output values.

DESCRIPTON OF THE CONTROLLED OBJECT

We used a project «Tanks 1–12» in SCADA-system at OJSC «Savushkin product» as site to test neurocontroller. This project controls pasteurization machine N2 (Fig. 1).

Brief description of pasteurization process: milk from an input tank is fed to the lamellar heat exchanger P1 by the pump N101. Here it is heated and goes to a homogenizer, after is pasteurizing in the tubular heat exchanger T1. Control is in keeping temperatures TE100 (homogenization) and TE101 (pasteurization) in desired limits by opening controlled steam valves VC100 and VC101.

Fig. 1. General view of the pasteurization machine № 2

Controlled steam valves working range varies from 0% – fully closed, to 100% – fully opened. The temperature TE100 must be in limits 75±2 ºC, TE101 – 95±2 ºC

PASTERIZATION MACHINE NEUROCONTROLLER

As neurocontroller we chose multilayer perceptron with structure: 30 inputs, 15 hidden elements, 1 output; activation function for hidden layer – sigmoid, for output layer – linear (Fig. 2). For leaning we used saved data – first 300 data points, 10 – window size. After this step learned net prognoses control signal.
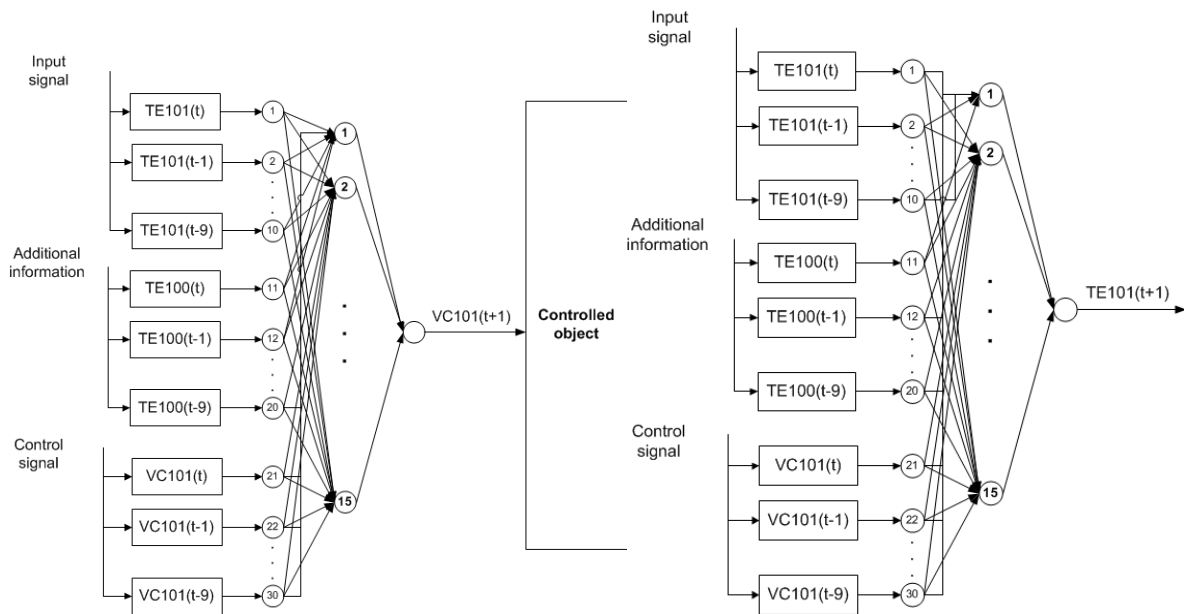
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Fig. 2. The pasteurization machine N2 neurocontroller (left) and neuroemulator (right)

We learned system with accuracy 0.02 and 0.0015. The learned neurocontroller can be used instead of the conventional PID.

PASTERIZATION MACHINE NEUROEMULATOR

As neuroemulator we chose multilayer perceptron with structure: 30 inputs, 15 hidden elements, 1 output; activation function for hidden layer – sigmoid, for output layer – linear (Figure 2).

Preliminary off-line learning: for leaning we used saved data – first 300 data points, 10 – window size. We learned system with accuracy 0.003 and 0.001. After this step learned net prognoses system output.

On-line learning: we used preliminary learned neuroemulator with accuracy 0.003. During work neuroemulator is learnt every 5-th time step by one learning iteration.

The learned neuroemulator can be used as the model of the pasteurization machine. What's more, it can self-tune with time adjusting to changing conditions.

RESULTS

The designed controllers were embedded into the project "Tanks 1-12" in SCADA-system at OJSC "Savushkin product". Figures 11 and 12 shows pasteurization machine work.

Neuroemulator. At the first phase we used neuroemulator after off-line learning. On the plot part, which used for learning (work mode - pasteurizing), the neuroemulator is closely to output temperature. But on the other parts (work mode – cleaning and others) neuroemulator has some constant offset in comparison to output temperature. This offset value depends on the work mode. It is because the pasteurization machine tunes in the new mode and work conditions are changing. To solve this problem we used on-line learning. Figure 3 shows new results.
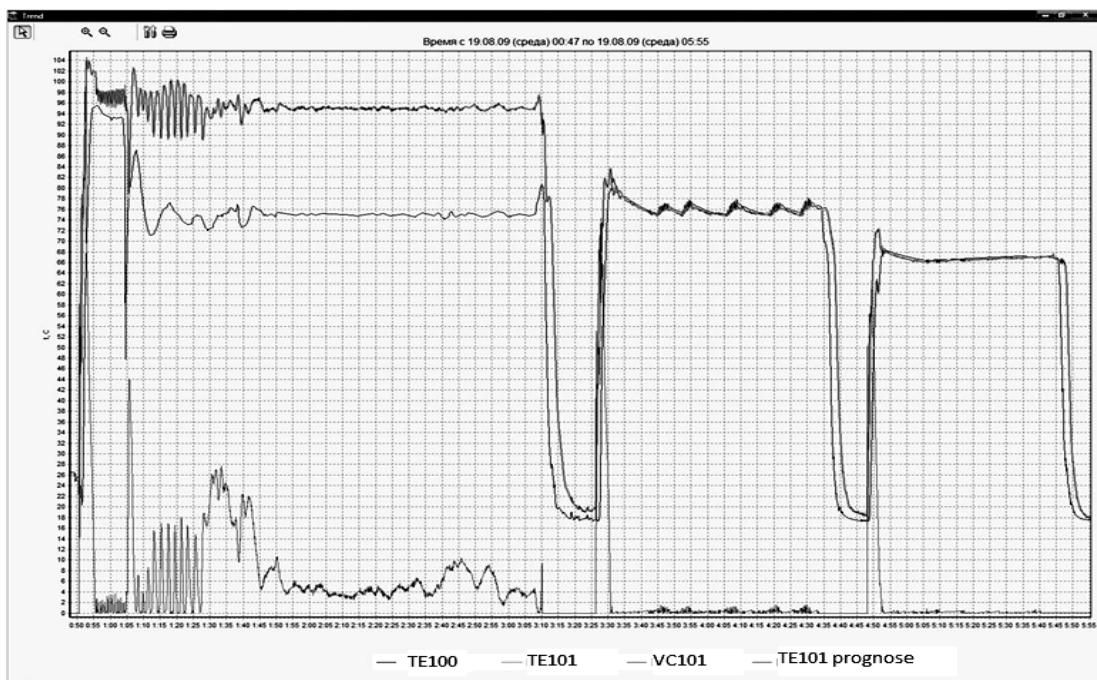
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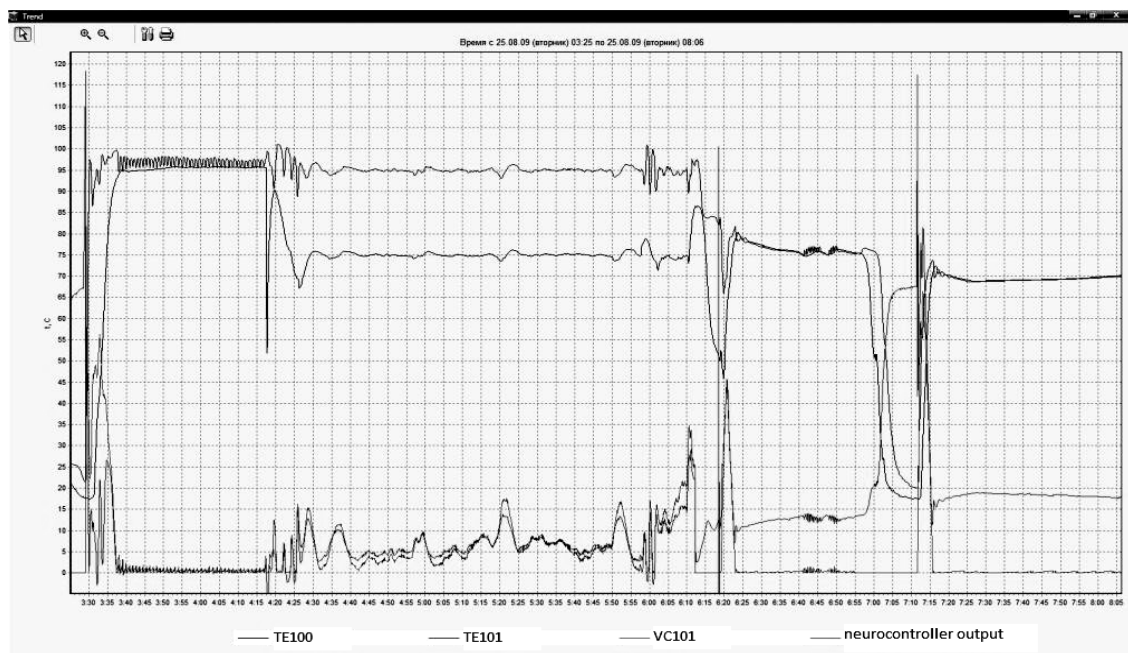*Fig. 3.* Neuroemulator. Pasteurizing machine N2 work diagram

Fig. 4. Neurocontroller. Pasteurizing machine N2 work diagram

On-line learning uses this algorithm: if during three steps of work prognosis error is more than 0.5 °C than one learning iteration is performed. So the neuroemulator accuracy is good in spite of the work mode.

Neurocontroller. As we can see on the plot part, which used for learning (work mode - pasteurizing), neurocontroller is closely to PID (Fig. 4).

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But on the other parts (work mode - cleaning) neurocontroller has some constant offset in comparison to PID. This offset value depends on the work mode. It is because the pasteurization machine tunes in the new mode and work conditions are changing.

To solve this problem we should combine neurocontroller and neuroemulator (future work).

CONCLUSIONS

There are many problems about the ways of enhancing the control systems. Usage neural networks are proposed as alternative way of using standard PID controlled systems. The structure of such systems was given. The neurocontroller has a good effect in comparison with the conventional PID controller. Testing showed the effectiveness and fast response. Future work will be connected with implementation of self-learning "on-the-fly" neurocontroller without off-line learning.

LITERATURE

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