ADAPTIVE CONTROL OF HOT-AIR LABORATORY MODEL USING ARTIFICIAL NEURAL NETWORKS

Ing. Václav VELEBA, Doctoral Degree Programme (1)
Dept. of Control and Instrumentation, FEEC, BUT
E-mail: xveleb00@stud.feec.vutbr.cz

Supervised by: Prof. Petr Pivoňka

ABSTRACT

The real application of the neural network as a control and estimation element was described. Two parameters can be controlled in a laboratory hot-air system – the airflow and the temperature inside the tunnel. The controlled system displays ordinary negative effects encountered in industrial applications. When the basic approaches to control using neural networks had been studied, a new control algorithm - semi-inversion controller was designed. The controller is capable of solving problems such as oscillating control action, noise sensitivity and ill-estimated parameters in the initial phase of control or adjustment.

1 INTRODUCTION

Application of neural networks for process modeling and control has started in the past decade. Modern approaches such neural networks or fuzzy logic can be applied where the conventional techniques fail. A major application in these cases is control of non-linear high noise-level physical systems, such as the laboratory model of hot-air tunnel. The system displays negative effects encountered in industrial applications: different static amplifications at different operating points, a large temperature offset, dead zone and noise. The described negative effects hinder application of conventional techniques such as STURE with the least-squares method (RLS) [2]. During the control process (on-line), adaptive control should be able to identify a system by monitoring inputs and outputs, and subsequently design an appropriate control algorithm structure. The semi-inversion neural controller first described in [1] was used in the hot-air system. It is based on the frequently described inverse neural controller, but is capable of eliminating problems such as extremely oscillating control action, high noise sensitivity and an ill-trained model of the system in the initial phases of control.

2 SEMI-INVERSION NEURAL NETWORK-BASED CONTROLLER

A detailed description of the semi-inversion controller and derivation of consequent formulas is in [4]. The internal structure of the semi-inversion controller is shown in Fig. 1. The semi-inversion model has been tested on correctly behaving linear systems.

The neural model output of the system can be described as follows

$$\hat{y}(k) = a_1 y(k-1) + \cdots + a_n y(k-n) + b_0 u(k) + \cdots + b_m u(k-m) + \theta \tag{1}$$

where a_i and b_i are coefficients of the system linear model, θ is its offset. When the neural network of the linear perceptron type is used, the coefficients are its weights. An example of the linear model connection for a third-order system is in Fig. 2 on the left.

The neural controller using the same coefficients and its relationship is

$$u(k) = b_0 e(k) + a_1 e(k-1) + \cdots + a_n e(k-n) + b_1 u(k-1) + \cdots + b_m u(k-m) - \frac{1}{\theta_{corr}}\theta \tag{2}$$

where θ_{corr} is the system offset correction. It can be applied if the system offset is zero or if there is a defect. An example of connecting the neural controller for a third-order system is in Fig. 2 on the right. Offset correction is computed from denominator of controlled system model.

$$\theta_{corr} = \frac{b_0 + \cdots + b_m}{1 - b_1 - \cdots - b_m} \tag{3}$$

The semi-inversion controller was originally designed for control of systems with unit amplification. In systems with other than unit amplification, the control offset must be divided by the open loop amplification A.

$$A = A_{sinv} \cdot A_S = \frac{b_0 - \sum_{i=1}^{n} a_i}{1 - \sum_{i=1}^{m} b_i} \cdot \frac{\sum_{i=0}^{m} b_i}{1 + \sum_{i=1}^{n} a_i} \tag{4}$$

We can use with advantage the modified feedback for controller e_M, which enables us to modify the shape of the step response curve:

$$e_M = d(k) + \gamma\left[d(k) - y(k-1)\right] \tag{5}$$

where γ is the feedback-elasticity coefficient. By changes of γ we can set velocity and step response with or without overshoot.

3 THE EFFECT OF AN OVER-TRAINED NEURAL NETWORK ON ESTIMATING THE CONTROLLED SYSTEM PARAMETERS

In neural model training to the controlled system, dynamics there are two contrasting requirements: The fastest possible training to unknown dynamics and restrict model to train the noise. The first objective can be achieved by increasing the number of iterations in each

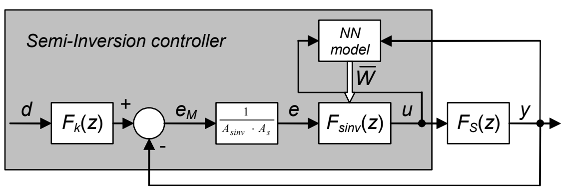

Fig. 1: *Semi-inversion controller inner structure*

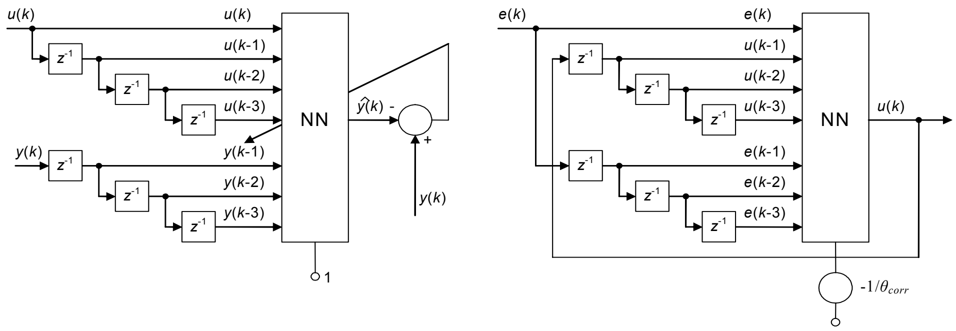

Fig. 2: *An example of connecting neural network inputs for third-order system control, on the left – neural model connection, on the right – controller connection*

sampling period until the model output (predicted output) is be exactly the same as the system output. In simulations with noise and in real system control this solution proved to be utterly ineffective. The estimated parameters oscillate, and convergence to the correct parameters is slow. Moreover, if applied directly in the controller design, they cause control action oscillation. The most acceptable solution is decreasing the number of training steps and slightly increasing the length of the training set [3]. Then the BP algorithm will be able to filter the noise in the training set. This process is simulated in Fig. 3. An adaptive semi-inversion controller has been used for control of a system with additive white noise on the output. In Fig. 3 on the left, we can see the time series of estimated parameters for 100 epochs and in Fig. 3 on the right the same series for 1000 epochs. Due to the decreased number of training epochs, the estimation of parameters is worse in the initial stages of identification. It is therefore desirable to either use a controller with preset parameters and switch to an adaptive controller after some time, or use a semi-inversion controller less sensitive to incorrect initial estimation.

4 HOT-AIR TUNNEL

The hot-air system laboratory model is a MIMO dynamic system. Fig. 4 shows the hot-air system block diagram. The model is connected to the programmable logic controller B&R controlling its actuators and measuring signals from the sensors.

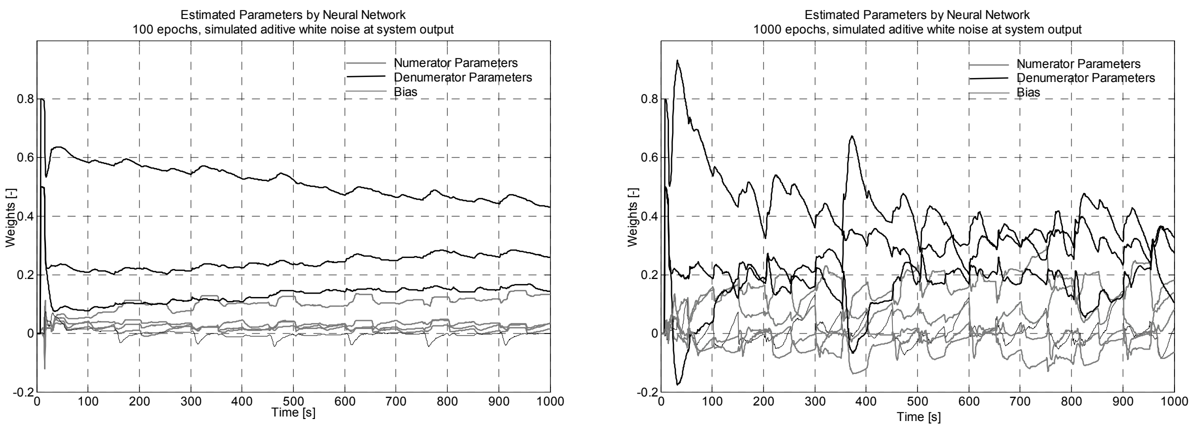

Fig. 3: *Time series of estimated parameters for different numbers of training epochs, left – 100 epochs, right – 1000 epochs*

The voltages of actuators and controlled variable sensors are standardized using adjustment circuits at 0÷10 V. The system consists of three actuators – a heating lamp affecting the temperature and brightness in the tunnel and two ventilators – a large one (further only ventilator), which causes air flowage in the tunnel axis and a small one orthogonal to the axis and cooling the lamp and the thermistors. Three parameters can be controlled – temperature (measured by three thermistors in different spatial configurations towards the lamp), air flowage (measured by vane flowmeter and resistivity based anemometer) and light flow (photoresistor measured).

The semi-inversion controller algorithm was used to control the following transfer functions:

4.1 HEATING LAMP- THERMISTOR TRANSFER FUNCTION

The voltage on the heat lamp affects the temperature in the tunnel. There are three measuring sites – thermistors at different distances from the lamp. The air flow from the ventilator cools the system and consequently a control disturbances occurs. Simultaneously the noise level is increased. Another negative effect is the ambient temperature, and mainly the measuring current. The thermistor does not work in purely zero-current mode, and is heated during long measurement. This defect is manifested as a temperature drift and it often reaches 2.5 V. In order to eliminate it the small fan is used. It can cool not only the lamp, but partially also the thermistors. The transmission lamp-thermistor has first-order dynamics.

4.2 VENTILATOR-VANE FLOWMETER TRANSFER FUNCTION

By rotating the ventilator, we can control the air flowage in the tunnel. The air flowage rotates the flow sensor vane, and an optoelectronic sensor scans rotations. The rotations are proportional to the air flowage. Air flowage generated by the small fan can be considered a disturbance, but its effect is relatively low. Increasing or decreasing the power input of the heating lamp is negligible. The transmission fan-vane has second-order dynamics. The action element fan exhibits 5÷8 % dead zone at the initial point of coordinates.

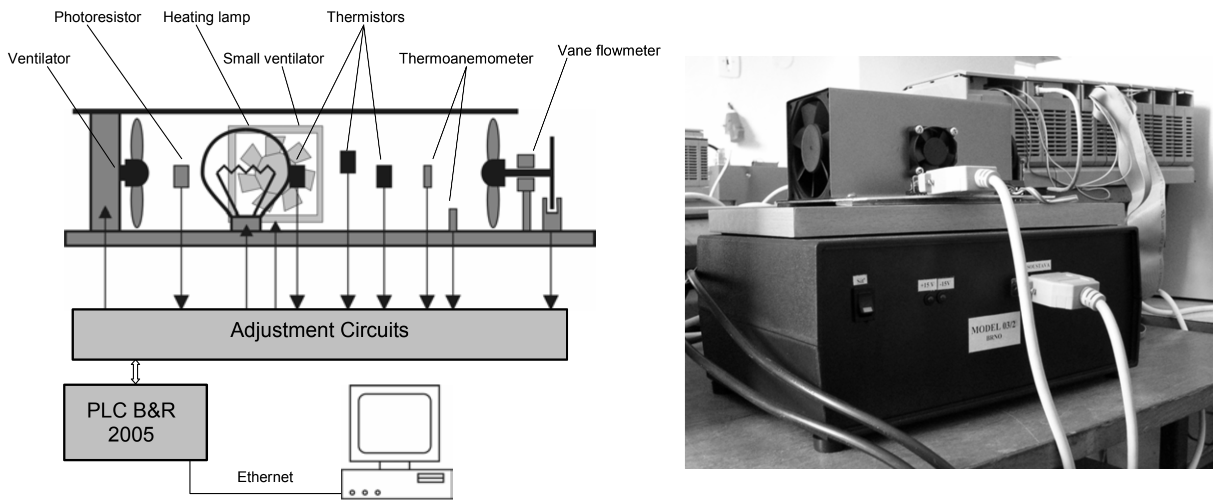

Fig. 4: *Laboratory model of hot-air tunnel*

5 HOT-AIR SYSTEM CONTROL

The control algorithm described in part 2 was used for control of both types of transfer functions described in sections 4.1 and 4.2. For correct verification of the controller efficiency, only minimum prior information on the controlled system was incorporated in the algorithm - information on the sampling period (0.5 s) and information on the control action range. Although it seems to be of advantage to apply a pre-trained neural model of the system at the start of adjustment, all neural model weights were set to zero. An appropriately pre-trained model will positively affect its behavior at the start of adjustment and the convergence velocity of estimated parameters. On the other hand, in this way set network may drop to the local minimum.

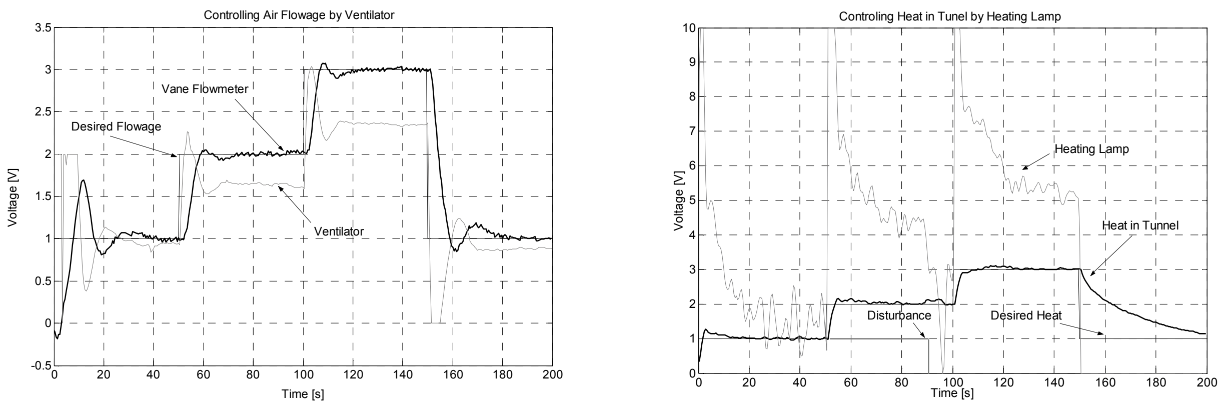

Fig. 5: *Semi-inversion control of hot-air system*

6 CONCLUSIONS

In the previous sections of this paper, we described an application of the adaptive semi-inversion neural controller for a laboratory hot-air system model. The semi-inversion controller originally designed for linear systems proved to have favorable characteristics also for considerably non-linear systems. The robustness and high degree of controller adaptability are shown in Fig. 5. A similarly set controller was, without major adjustment (only control action restriction) applied for control of two different physical parameters: tunnel temperature and air flowage.

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