



Dynamic prediction and control of heat exchangers using artificial neural networks

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Abstract

We extend the artificial neural network (ANN) technique to the simulation of the time-dependent behavior of a heat exchanger (HX) and use it to control the temperature of air passing over it. The experiments are carried out in an open loop test facility. First a methodology is proposed for the training and prediction of the dynamic behavior of thermal systems with heat exchangers. Then an internal model scheme is developed for the control of the over-tube air temperature with two artificial neural networks, one to simulate the heat exchanger and another as controller. An integral control is implemented in parallel with the filter of the neural network controller to eliminate a steady-state offset. The results are compared with those of standard PI and PID controller. There is less oscillatory behavior with the neural network controller, which allows the system to reach steady-state operating conditions in regions where the PI and PID controllers are not able to perform as well. © 2001 Elsevier Science Ltd. All rights reserved.

1. Introduction

Most simulations of heat exchangers and other components of thermal systems have concentrated on their steady-state behaviors for heat rate predictions which are required for system design. The dynamic response of these devices, however, is also very important if these devices are to be controlled in any way. For example, and this is the one that will be taken up here, a hot water heat exchanger may be required to provide heated air at a pre-set temperature that does not change even though the incoming air or the water may vary in either flow rate or temperature. In other control applications, the heat rate may be the parameter that is set.

Heat exchangers (HXs) are extremely complex devices for which the prediction of their operation from first principles is virtually impossible. There are a large number of phenomena associated with flow and heat transfer that are perhaps simple to solve singly, but when combined result in a system that is impossible to compute. Some of these are: complicated heat and fluid

flow geometries, turbulence in the flow, existence of hydrodynamic and thermal entrance regions, non-uniform local heat transfer rates and fluid temperatures, secondary flows in the tube bends, vortices in the neighborhood of the tube-fin junctions, air-side flow development in fin passages, heat conduction along tube walls, natural convection within the tubes and between fins, and temperature dependence of fluid properties [1]. Thus, even steady-state predictions are not easily made from a first principles analysis. Dynamic predictions are, of course, harder and it was not until recently that dynamical models started to appear in the literature [2–4]. Most of them, in order to make the problem more tractable, rely on assumptions and simplifications that are not totally realistic [5–7]. The results thus are qualitative rather than quantitatively exact. Some of the most common assumptions are: lumped thermal conditions, constant fluid properties, constant heat transfer coefficients, constant flow rates, complete transverse mixing in the flow, negligible heat conduction in the wall, negligible heat conduction through the fins, and negligible heat capacity of the wall [4]. The models that include more physics are usually partial differential and their time-dependent solutions are computationally intensive and are not suitable for real-time control purposes. Another difficulty is that the performance of a typical

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Nomenclature			
c	specific heat [J/kg K]	\dot{Q}_{cor}	heat transfer rate predicted by power-law correlations [W]
C	ANN controller	t	time [s]
$f(t)$	time-dependent forcing function	Δt	time step [s]
F	robustness filter	T	temperature [°C]
I	integral control	$x(t)$	variable in differential equation
\dot{m}	mass flow rate [kg/s]	x_0	initial condition
M	ANN model of the plant		
n	order of the ANN approximation	<i>Subscripts and superscripts</i>	
P	real process or plant	a	air side
\dot{Q}	heat transfer rate between fluids [W]	in	inlet
\dot{Q}_{ANN}	heat transfer rate predicted by ANN [W]	out	outlet
		w	water side

HX slowly changes over time due to such factors as fouling that changes the heat transfer characteristics of surfaces.

Artificial neural networks (ANNs) have been used in recent years to avoid the problems associated with deterministic approaches, and have been shown to approximate nonlinear functions up to any desired level of accuracy [8]. They are also less sensitive to noise and incomplete information than other approaches such as empirical models and correlations. In recent years, the technique has been applied to many thermal problems [1], among them the prediction of the steady state [9] and the dynamic behavior of heat exchangers [10–12]. The advantage of using ANNs to simulate thermal processes is that, after they are trained, they represent a quick and reliable way of predicting their performance. They can also be continuously updated. Thus, if we apply this technique to the problem of simulation and control of HXs, then we obtain an accurate prediction with a short computational time for the simulation which can be used in an efficient real-time control scheme.

There are several schemes that have been proposed for the neural control of nonlinear systems [13–16]. One of these is a method called internal model control (IMC) [17–19]. This technique has been used for a variety of problems in different areas due to its excellent characteristics of robustness and stability [20]. The IMC technique using ANNs consists of training a network to learn the dynamics of a process, after which another ANN is trained to learn the inverse dynamics so that it can be used as a nonlinear controller [17,21].

In this work, we use the combined advantages of ANNs and IMC to generate an efficient real-time control scheme for a HX installed in a test facility. The HX transfers heat from water to air, and the objective is to control a single output variable, the outlet air temperature, by changing a single input variable, the air speed. The system consists of the HX and the entire water- and air-flow subsystems. The results of the neural control are

compared with those of standard PI and PID techniques.

2. Background

2.1. Experimental setup

The experimental setup consists of a variable speed wind tunnel facility located in the Hydraulics Laboratory at the University of Notre Dame (details are in [22]). A single-row water-to-air fin-tube heat exchanger is used to obtain static and dynamic measurements. Fig. 1 shows a picture of the experimental facility. There is a single water-side circuit which goes back and forth across the face of the heat exchanger. This is a nominal 18 in. \times 24 in. type T water coil heat exchanger manufactured by Trane. Type-T isolated thermocouples are used to measure the inlet and outlet temperature of the air and water side. The motion of the air in the tunnel is due to a fan that is controlled by a variable speed drive that can be operated manually or automatically from a personal computer. The air speed is measured using a Pitot tube, located upstream of the heat exchanger, that is connected to a differential pressure transducer. The filter and data acquisition board used can obtain measurements of up to 16 different channels, simultaneously. The data acquisition board receives information about inlet and outlet temperatures of both the air and water side, the mass flow rate of water, the air speed and the time at which the measurements were taken. The inlet water temperature is varied by using a heater with a PID-controlled electrical resistance. The water flow rate is modified by an electronic valve so that the percentage of opening can be controlled as desired from the personal computer. LabVIEW is used to acquire and send data to the experimental system and an interface was built in C language to simulate the neural networks and perform the desired control action. Time-dependent

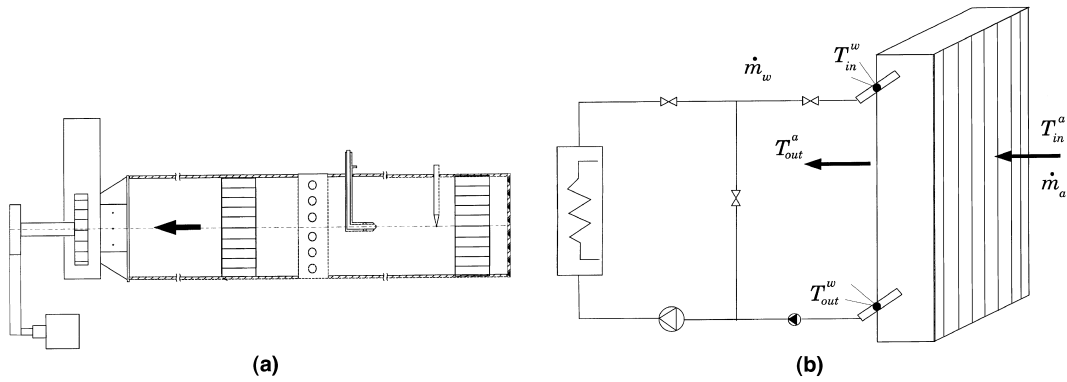


Fig. 1. Experimental setup: (a) wind tunnel; (b) heat exchanger.

information regarding the air and water mass flow rates, \dot{m}_a and \dot{m}_w , respectively, the air and water inlet temperatures, T_{in}^a and T_{in}^w , respectively, and the air and water outlet temperatures, T_{out}^a and T_{out}^w , respectively, are stored.

2.2. Artificial neural networks: steady-state simulations

The description, training and operation of ANNs are available in many recent texts [23]. Input and output data have to be supplied to the network so that it can be trained by using an algorithm that can adjust its internal weights and biases. It can be shown that multilayer networks are universal approximators capable of approximating any measurable function to any desired degree of accuracy [24]. Here, the variables to and from the ANN are normalized to be within a [0.15,0.85] range. Although there are other methods, the back-propagation algorithm [25] is one of the most common learning methods used to train ANNs. We use it because of its well-known adaptation and generalization characteristics even though other algorithms can lead to more accurate models.

In the steady state, the ANN predicts the heat rate under given conditions. The steady-state heat transfer rate, \dot{Q} , was determined from the measured temperatures by

$$\dot{Q} = \dot{m}_w c_w (T_{in}^w - T_{out}^w) = \dot{m}_a c_a (T_{out}^a - T_{in}^a),$$

where c_a and c_w are the air and water specific heats, respectively. Since the air and water sides give slightly different \dot{Q} (within 10%) an average value is used.

An ANN, shown schematically in Fig. 2(a), was trained with \dot{m}_a , \dot{m}_w , T_{in}^a and T_{in}^w as inputs and \dot{Q} as output. Fig. 2(b) shows a comparison between the heat transfer rates obtained with the ANN, \dot{Q}_{ANN} , and those measured, \dot{Q} . Predictions obtained with a heat transfer correlation, \dot{Q}_{cor} , that was found earlier for the same HX [22] are also included. It is observed that the ANN prediction is superior to that of the correlation. It must

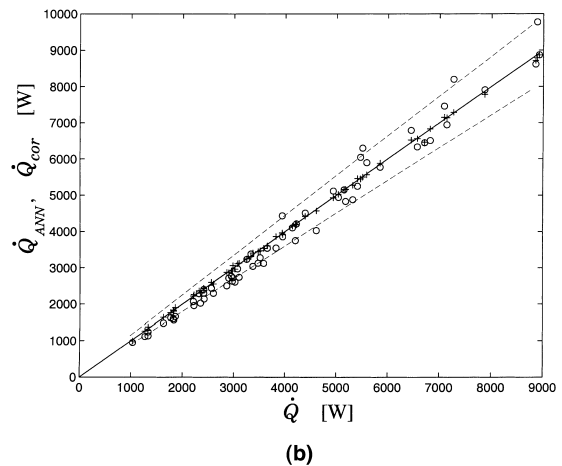
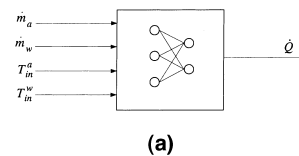


Fig. 2. Steady-state predictions: (a) inputs and output; (b) comparison with measurements; o correlations, + ANN (4–5–5–1); dotted lines are $\pm 10\%$ deviations.

be pointed out that some of the measurements had about 10% error; the predictions merely reflect this inherent inaccuracy in the data since they cannot of course be better than the measurements. More about steady-state predictions for thermal systems using ANNs are in Díaz et al. [9].

2.3. Artificial neural networks: dynamic simulations

For control purposes, it is not enough to have steady-state predictions, since the process is really time-dependent. It is thus of interest to extend the capabilities of the

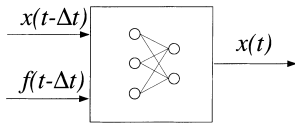


Fig. 3. Training method for dynamic problems.

ANN technique to dynamic simulations. This can be done training the ANN providing it with the information of the dynamic behavior as shown in Fig. 3. In this method, no explicit information about time is provided to the network; the variables involved in the problem are presented at time $t - \Delta t$ as an input to the network and the output corresponds to the variables at time t .

3. Dynamic predictions

The dynamic ANN developed in the previous section is now used to predict the behavior of the HX. The inputs to the network are \dot{m}_a , \dot{m}_w , T_{in}^a and T_{in}^w and the output is \dot{Q} . Fig. 4 shows the comparison between the ANN prediction of the water and air outlet temperatures, using the training method and five different training curves, and the actual measurements for a step change in the water flow rate. The first dip in the shape of the T_{out}^w curve is due to the presence of the mass of water that was located within the HX when the water flow was shut down. The second dip in T_{out}^w is due to the same mass of water but after going through one lap in the water circuit. As its initial temperature was close to T_{in}^a , the heater is not able to raise its temperature to the desired value after only one lap of the water circuit. However, good predictions are achieved for both the water and air side of the HX. Fig. 5, on the other hand, shows the comparison between the ANN prediction, using five training curves, and the measurements taken for a cooling process in which the heater is shut off.

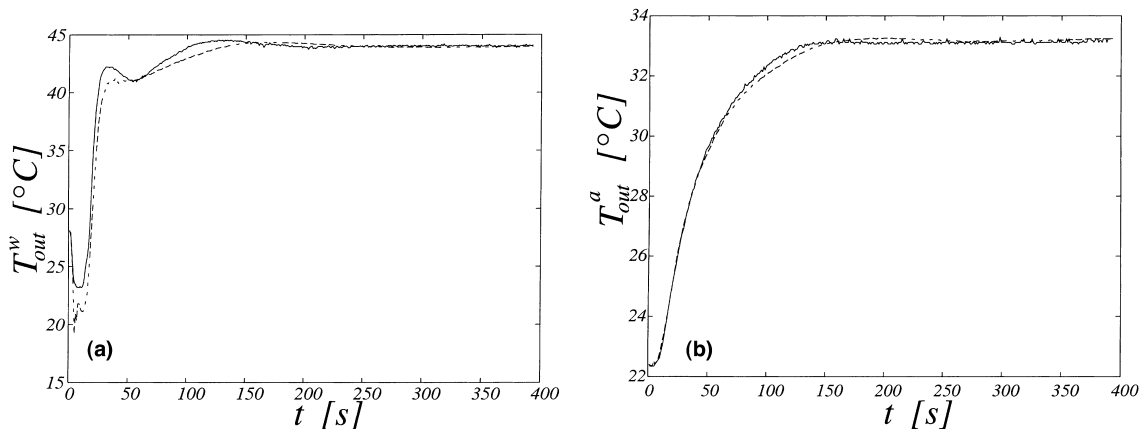


Fig. 4. Prediction of transient heating: — experiment; - - ANN (4-5-5-2).

One important aspect that has to be considered when modeling the dynamics of a system is its order. We have to provide values of the relevant variables at previous instants in time. This is because the ANN is simulating an differential equation of unknown order. The higher the order, the larger the number of previous instants for which information must be provided as inputs. Enough past information at previous instants in time that is appropriate for the actual order of the system must be provided, as shown in Fig. 6(a), where n is the order of the system. This is experimentally verified in Fig. 6(b) which shows time-dependent predictions of T_{out}^a for increasing assumed order of the system. In each experiment, the air speed was decreased in five small steps and then similarly increased in small steps. Both the experimental measurements and the ANN predictions are shown; the temperature is in normalized units and the time is in terms of the sample number s . The prediction is seen to improve as we go from $n = 1$ to $n = 2$, but there is little observable difference between $n = 2$ and $n = 3$. These measurements indicate that the order of the system, if one has to choose an integer, is probably two and it is not necessary to assume a higher value.

4. Temperature control

We now proceed to design an algorithm to control T_{out}^a . This can be achieved by controlling one or more of the variables \dot{m}_w , \dot{m}_a , T_{in}^w , and T_{in}^a . In this work, we confine ourselves to a single-input–single-output system, and for ease of experimentation we have chosen \dot{m}_a as the control variable while keeping the others fixed. The relationship between \dot{m}_a and T_{out}^a is nonlinear and complicated. Strictly speaking, it is a solution of a partial differential equation in space and time. Some idea of the nonlinearity of this equation can be obtained by looking at the steady state, for which a heat balance gives

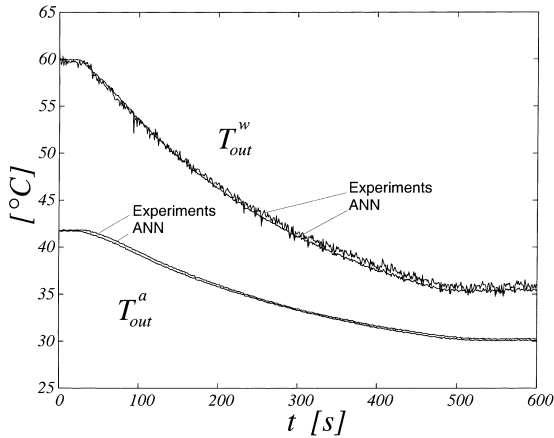


Fig. 5. Prediction for transient cooling; ANN (3–5–5–2).

$$T_{out}^a = \frac{1}{\dot{m}_a c_a} \dot{Q} + T_{in}^a,$$

where \dot{Q} is the heat rate which also depends on \dot{m}_a . Fig. 7 shows the measured function $T_{out}^a(\dot{m}_a)$ for different \dot{m}_w .

The slope of the curve changes considerably with \dot{m}_a indicating that the sensitivity of the system depends on the operating point.

There are other difficulties that increase the complexity of the nonlinear control problem. First, the system that we are controlling includes not only the HX but also its associated hardware, i.e. fan, pump, PID-controlled heater and measuring instruments such as a water flow meter and a pressure transducer. Second, there is a delay between what happens at the HX and the measurements of T_{out}^a since it takes a while for the air to flow from the HX to the point of measurement. As the air speed slows down this delay is longer and it is harder to control the air temperature. Finally, there is a gradual change in the HX characteristics due to fouling effects. ANNs are very well suited for these tasks because they can be taught to learn the response of the system.

4.1. ANNs with IMC

IMC consists of having a model of a plant M in parallel with the real system P , as shown in Fig. 8. The

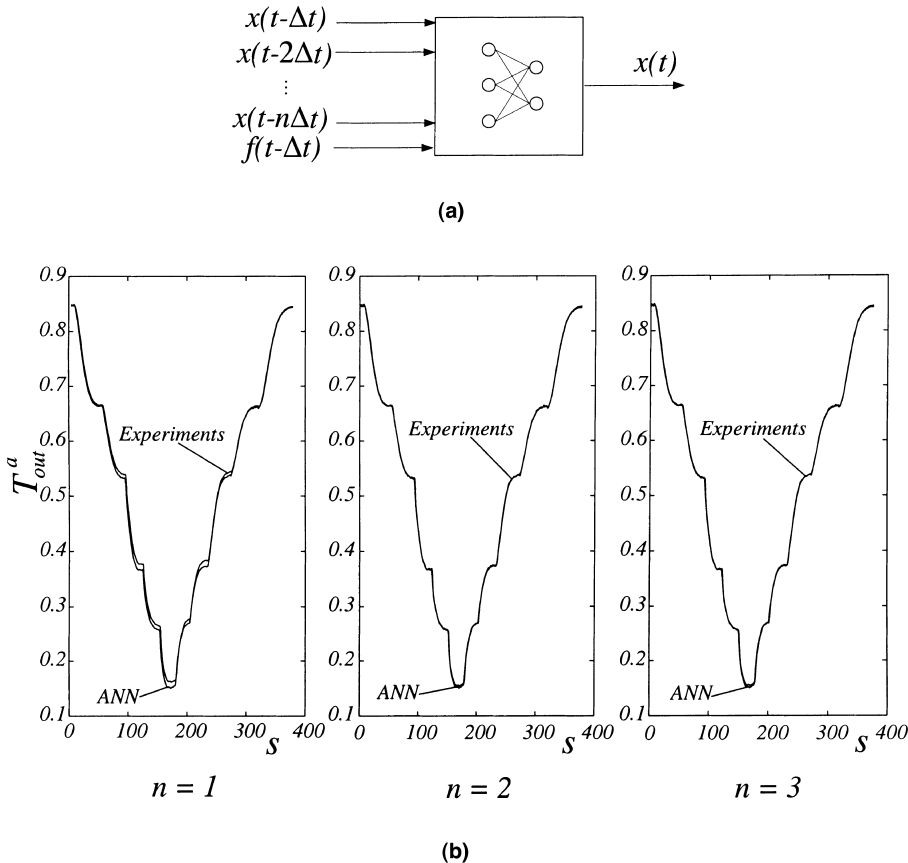


Fig. 6. (a) Training a system of order n . (b) Response of HX treated as a system of different orders. T_{out}^a is normalized and s is the sample number.

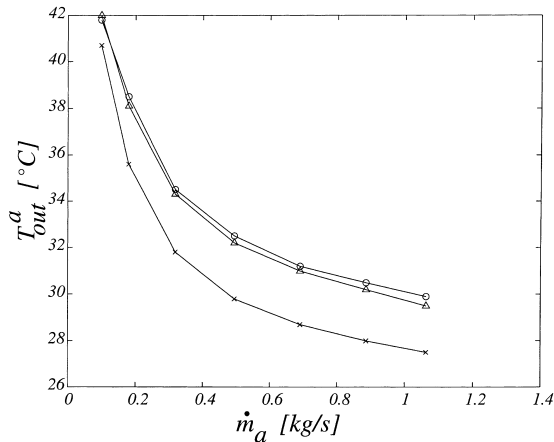


Fig. 7. Nonlinear relation between \dot{m}_a and T_{out}^w for different mass flow rates of water. —○— 260 kg/s, —△— 200 kg/s, —×— 65 kg/s.

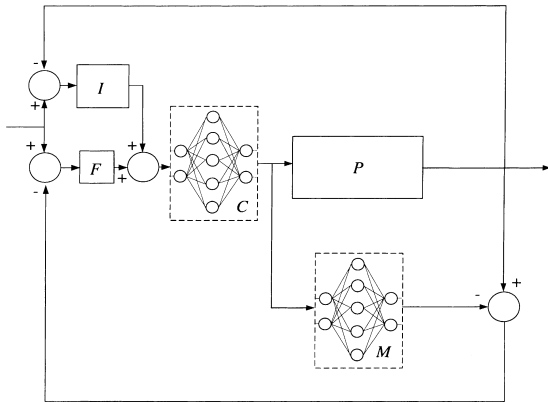


Fig. 8. General IMC structure plus integral control

difference between the outputs of P and M is used as the feedback for a controller C that is located in the forward path of the control scheme. The training procedure of such a control system using ANNs has two steps:

- We first train an ANN to learn the dynamics of the process by providing known input and output data sets. This is M .
- Then, another ANN is trained to learn the inverse dynamics of the process and to function as a nonlinear controller C . It is trained to invert the model M instead of trying to learn the inverse dynamics of the actual process. By training in this way, we make sure that we invert the steady-state gain of the model so that the offset can be eliminated.

For our experiments, we trained the plant model M with information related to T_{out}^a and \dot{m}_a . These data

were obtained by taking measurements of the system subject to small increments in the setpoint temperature. The controller C is obtained by using a synthetic signal which is the desired value of the air speed. This signal is supplied to M to give a certain value of T_{out}^a which is then supplied as the input to the controller. The training algorithm adjusts the weights of C to reduce the error between the synthetic signal and the controller output.

Since the ANNs only provide an approximation to the behavior of the actual plant, we used a one parameter filter F , following the suggestion of Nahas et al. [18], preceding the controller in the forward path to account for plant-model mismatch. An integral control path I was also added in parallel with F to help obtain an offset-free controlling action (an initial control scheme without it failed to provide offset-free control). There are two constants that have to be chosen by trial and error, the first for the integral controller and the other for the filter.

As a large percentage of the controllers that are currently being used correspond to proportional-integral and proportional-integral-derivative schemes, standard PI and PID controllers were used to compare the performance with the ANN controller. This was through a general purpose LabVIEW subroutine implementing a PID controller based in the relations developed by Shinskey [26], the optimal values of the PID constants being obtained using the tuning method also explained there. The derivative action can be shut down by means of setting the corresponding constant equal to zero. In this way, the same algorithm is used for both the PI and PID controlling schemes. The two different tests that were conducted are described below.

4.2. Comparison with PID: step change in setpoint

The first test was designed to observe the performance of the controller subject to a step change in the value of the setpoint temperature T_{out}^a . The system was taken up to a point in which the outlet air temperature was near 32°C. The controller was turned on and we waited for 40 s until the temperature remained within a band of $\pm 0.1^\circ\text{C}$. The setpoint was then increased to 36°C. Both controllers performed well and behaved in a similar way when controlling the system at large values of air speed. However, on approaching the lower end of air speeds, the system became very hard to control for two reasons. One is the effect of the delay involved, and the other is the high sensitivity of T_{out}^a to \dot{m}_a at low air speeds. This test brings the system from a very easy-to-control point at 32°C to a hard-to-control state at 36°C. The results are shown in Fig. 9. It is seen that, although the ANN controller has a slightly larger overshoot, it presents less oscillations

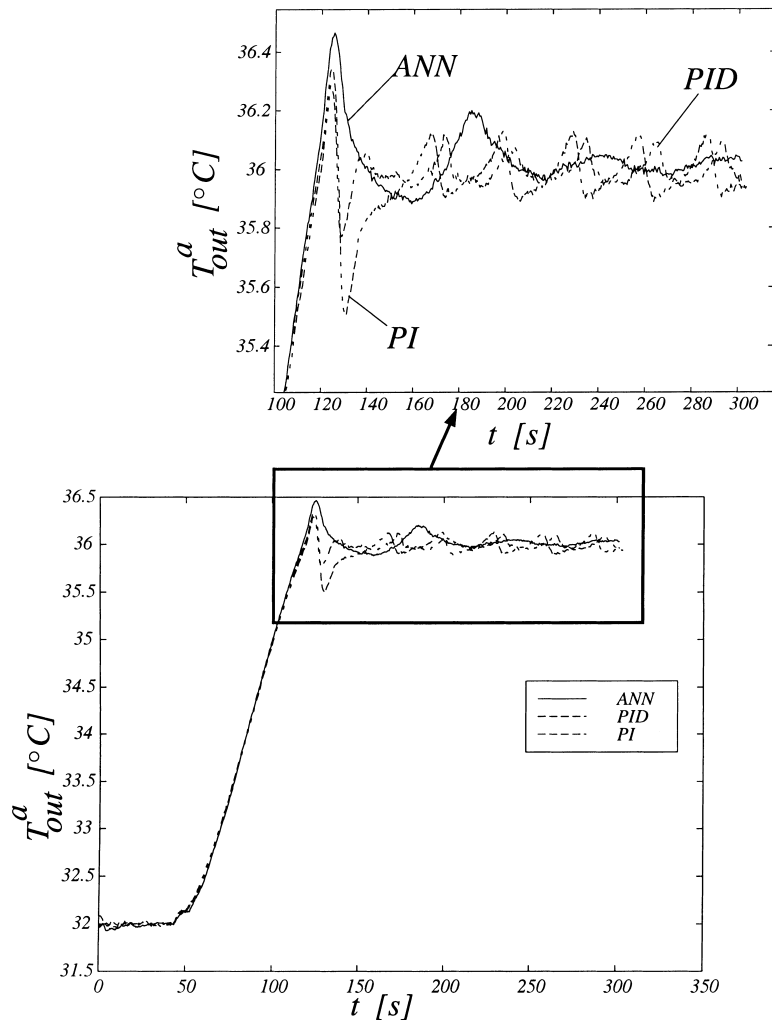


Fig. 9. Change in the setpoint temperature: — ANN; - - PID; -·- PI.

and it is able to bring the system to a stable condition. On the other hand, both PI and PID controllers oscillate significantly more and are not able to bring the system to a steady state, but keep T_{out}^a within 36°C by constantly adjusting the air speed. Thus, the ANN controller uses less energy and is more stable by keeping the system steady instead of generating an oscillatory controlling action.

4.3. Comparison with PID: disturbance rejection

We now analyze the disturbance rejection capabilities of the control system. In this test, a disturbance is applied to the plant in the form of a pulse in the following way. Once the system is at steady-state operation, we

shut down completely one of the valves on the water side for a short time. Once again, we test the controllers at a state that is hard to control, i.e. with $T_{\text{out}}^a = 36^\circ\text{C}$ and a low air speed. The PI controller showed the worst performance and is left out of the comparison shown in Fig. 10. Fig. 10(a) shows the change in the water flow rate which is the disturbance itself; the water flow is shut down between $t = 40$ and 70 s. After the disturbance pulse, the controller brings the system back to steady state. Figs. 10(b) and (c) show the change in T_{out}^a and \dot{m}_a , respectively. Once again it is seen that the PID is not able to bring the system to a steady-state condition while the oscillations of the ANN controller are quickly damped out. It is seen in Fig. 10(c) that the PID controller, in trying to control the temperature, generates an oscillatory air speed.

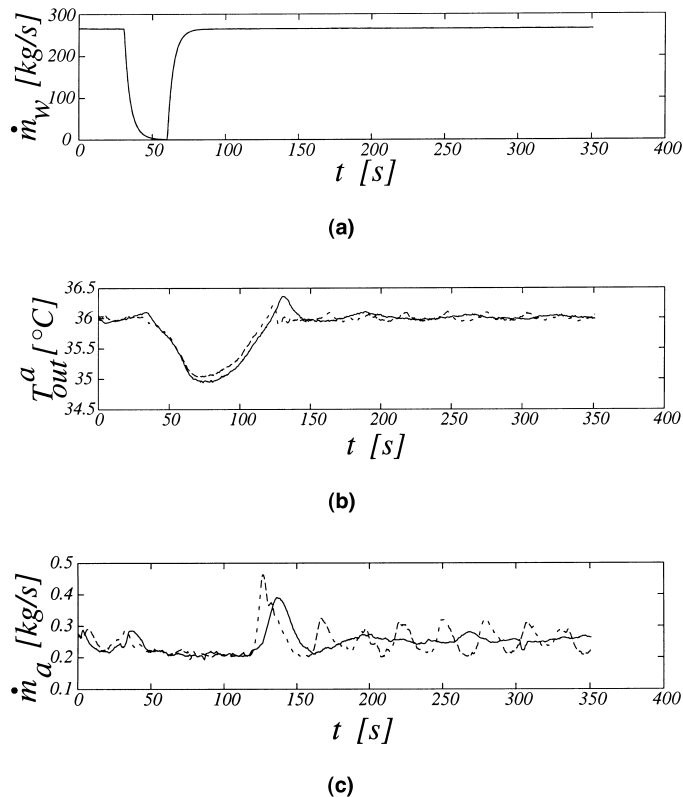


Fig. 10. Disturbance rejection: – ANN; - - PID.

5. Conclusions

Previous work has demonstrated the usefulness of the artificial neural network technique for the prediction of the steady-state behavior of heat exchangers. In the present, this technique is extended to the prediction of the dynamic behavior of a thermal system which consists of a heat exchanger working between a closed hot water and an open air loop. The dynamic network is then used, in conjunction with internal model control, to control the temperature of the air coming out of the heat exchanger. The tests showed that the present technique performed better than conventional PI and PID control in certain cases.

Neural networks are powerful tools for thermal control. They can be trained to simulate the behavior of a dynamical system and they are adaptive. In the present work, the network was trained off-line, but in the future on-line training will be incorporated to enable continuous learning and adaptation to changing conditions.

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