Adaptive Neurocontrol of Heat Exchangers

Gerardo Díaz[1]

Mihir Sen
Fellow ASME

K. T. Yang
Fellow ASME

Rodney L. McClain

Hydronics Laboratory,
Department of Aerospace and
Mechanical Engineering,
University of Notre Dame,
Notre Dame, IN 46556

This paper investigates the use of adaptive artificial neural networks (ANNs) to control the exit air temperature of a compact heat exchanger. The controllers, based on an internal model control scheme, can be adapted on-line on the basis of different performance criteria. By numerical simulation a methodology by which the weights and biases of the neural network are modified according to these criteria was developed. An ANN controller for an air-water compact heat exchanger in an experimental facility is then implemented. The parameters of the neural net are modified using three criteria: minimization of target error, stabilization of the closed-loop performance of the controller, and minimization of a performance index that we have taken to be the energy consumption. It is shown that the neural network is able to control the air exit temperature in the heat exchanger. The neurocontroller is able to adapt to major structural changes in the system as well as to simultaneously minimize the amount of energy used.
[DOI: 10.1115/1.1370512]

Keywords: *Artificial Intelligence, Control, Heat Transfer, Heat Exchangers, Systems*

1 Introduction

Most thermal systems present nonlinear dynamical characteristics that make them difficult to control. Heat exchangers (HXs) are one of these thermal components that present nonlinear behavior mainly due to complicated hydrodynamics and temperature dependence of fluid properties [1]. Because of these complexities the dynamics of HXs are difficult to model using first principles. This is not because the individual phenomena that play a role in the dynamics are not understood, but when they are all combined, the result is a complex system that is not easy to compute numerically [2]. For this reason, much of the information available about specific HXs is in the form of correlations that predict the steady state heat transfer [3]. On the other hand, even though numerical simulations based on simplifying assumptions may be possible [4], they are slow and thus not suitable for real-time control purposes. There is also need for a model that can adjust to the changes in the thermal system that occur over time, such as the those due to fouling in HXs.

The application of artificial neural networks (ANNs) to the simulation and control of thermal systems is currently of great research interest. This is a powerful technique to predict the response of physical systems that are too complex to be modeled from first principle analysis. They have been used to model the steady state [2] and dynamic [5] behaviors of HXs. They have also been applied to thermal systems for control purposes. Marwah et al. [6] address issues involved in the modeling of electronic manufacturing processes for optimization and control using artificial neural networks. Blazina and Bolf [7] used ANNs as a feedforward control for a two-stage heat exchange process; Ayoubi [8] used dynamic multilayer perceptron networks as the predictive model in model-based predictive control of a water-steam HX; Nahas et al. [9] used internal model control and ANNs to control the models of a continuous stirred tank reactor and a pH neutralization process; Chen et al. [10] used an adaptive single neuron to control a nonlinear and open-loop unstable model of a continuous stirred tank reactor. In this work, we deal mainly with the dynamics and control of thermal processes using ANNs. The interested readers are referred to Haykin [11] for further information about steady-state simulations and learning algorithms for ANNs.

It has been shown [12] that a trained ANN, even though its steady-state predictions may be accurate, may be unstable when used as part of a control system. Since we are interested in the on-line adaptation of an ANN controller, we will train it not only to minimize the target error but also to increase the stability of the resulting controller. In addition, in order to handle any optimal condition or conditions that may be imposed on the control, we will minimize a third criterion that in general can be user-defined. As a specific example that may be useful in certain applications, we will minimize the use of energy in the thermal system, though any other criterion can be used instead. The experimental facility in which the control system is installed uses a single-row fin-tube heat exchanger with water and air as the in-tube and over-tube fluids, respectively.

2 Neurocontrol

There are several control schemes that use ANNs as the dynamic model and/or the controller of a physical system [13]. Here, we have chosen to use the internal model control (IMC) approach because of its good characteristics of adaptation, robustness, and stability. The main objective of this paper is to show the excellent adaptive characteristics of neurocontrollers applied to thermal systems. We refer the reader to Díaz et al. [5] for details on the implementation of neuro-controllers for temperature control in heat exchangers, and to Díaz et al. [12] for the stabilization of their closed-loop performance during training. The ANNs in the previous work were all trained off-line before use; the present work is directed towards on-line adaptation of the ANN for optimum performance. The ANN is trained while it is performing its control function.

2.1 Internal Model Control. The idea behind IMC, shown diagrammatically in Fig. 1, is to have a model of a plant, indicated as ANN_1, in parallel with a real system. The difference between the output of the real system and the model is used as the feedback for a controller, shown as ANN_2, that is located in the forward path of the control scheme. In this case, ANN_1 and ANN_2 are neural networks. We first train ANN_1 to learn the dynamics of the plant. ANN_2 is then trained to learn its inverse dynamics in order to be used as a nonlinear controller. In the experiments, we trained ANN_1 and ANN_2 with information of the exit air tempera-

[1]Currently at Modine Manufacturing Co., Racine, WI 53403, g.c.diaz@modine.com

Contributed by the Heat Transfer Division for publication in the JOURNAL OF HEAT TRANSFER. Manuscript received by the Heat Transfer Division March 20, 2000; revision received January 8, 2001. Associate Editor: A. Bejan.

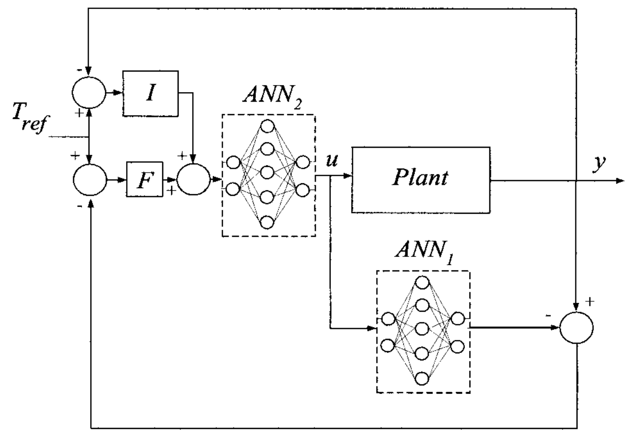

Fig. 1 IMC with integral control

ture from the heat exchanger, T^a_{out}, and the air speed, v_a, while keeping the inlet air and water temperatures and the water flow rate constant. These data were obtained by making measurements of the system subject to small increments in the set target point temperature. As we are working with a model of the plant, and since ANNs provide only an approximation to the behavior of the real system, we use a one-parameter filter, F, preceding the controller in the forward path which accounts for plant-model mismatch. An integral control structure, I, was also added in parallel with the action of F to help to obtain an offset-free controlling action. The filter F and the integral control I help the system to reach the actual setpoint temperature even with the destabilizing action of the noise embedded in the experimental measurements.

2.2 Adaptive Control. Adaptive control consists of automatically adjusting in real time the parameters of a controller so that a desired level of performance of a control system is achieved when the parameters of the process being controlled are unknown or vary with respect to time. The way to evaluate the performance of a control system is by selecting an index that will be compared with its desired value, the difference being fed back to activate the process of adaptation. The difference between conventional and adaptive control schemes is that the former reacts to disturbances acting upon the controlled variables and the latter to disturbances acting upon the parameters of the process [14]. Figure 2(a) shows the schematic of a non-adaptive controller compared to an adaptive controller shown in Fig. 2(b). In the present case, the adaptation is achieved by modifying the weights and biases of the two neural networks ANN_1 and ANN_2. It is done by carrying out single additional training cycles until the performance criteria are satisfied.

There are some issues relating to the different time scales involved in the problem that have to be addressed here. For instance, the plant has its own time scale for changes in its variables, and possibly more than one. On the other hand, the controller acts on actuators that have their own particular reaction time. Finally, if we want to implement an adaptive control system, we need to know how long ANN_1 and ANN_2 take to finish the adaptation process. Thus, if the adaptation period is long enough so that the physical system deviates from the desired set point in a significant way, we need a back-up controller that will keep the system as close as possible to the set point until adaptation is completed. In the experiments, the time scale of the adaptation process is the largest, that of the physical system intermediate, and the reaction time of the actuator smallest. Thus, we use a PID controller to keep the system under control until the ANNs adapt to the new operating characteristics of the plant. Because the plant may have a very different behavior due to its new characteristics, the PID controller keeps the system close to the set point. The constants of the PID controller are chosen, and kept fixed, for a certain behavior of the plant which may not be suitable for the system after the disturbance is applied; we only use it until the ANN controller has learned the new behavior.

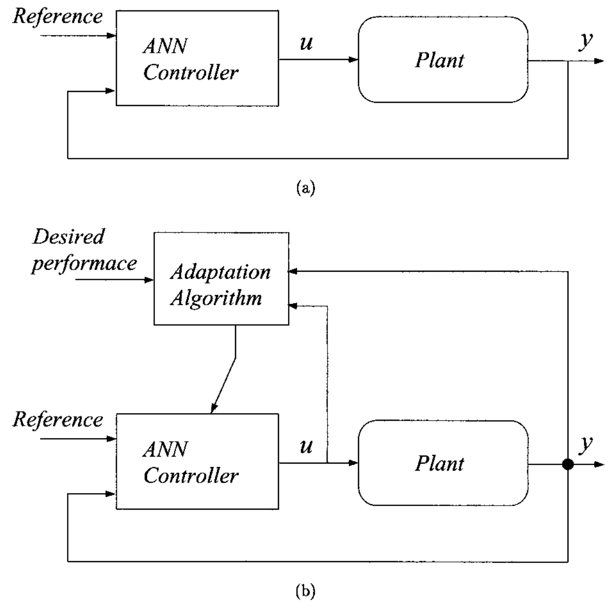

Fig. 2 Controllers: (a) non-adaptive, (b) adaptive

2.3 Simultaneous Minimization Criteria. One of the purposes of training an ANN is to minimize the target error between some known output and the prediction of the ANN with respect to a certain input. Since this ANN, if used as a controller within a closed-loop control system, may produce a dynamically unstable behavior, we must continuously check the stability of the closed loop system when training the ANN. For stability purposes, the closed-loop controller was treated as a nonlinear map that is iterated in time [12]. Its stability is checked by obtaining the spectral radius, r, of the Jacobian matrix of the map; $r<1$ indicates stability. As we modify the parameters of the ANN with respect to the target error and the spectral radius, we can also simultaneously consider other optimality criteria. For instance, we can use an index corresponding to the energy consumption for the particular plant and drive the system to an operating point where we achieve the desired temperature, obtain at the same time a stable controller, and also use the minimum rate of energy. If there are other functions that are needed to be minimized or maximized simultaneously, they can be treated in the same way.

3 Development of a Neurocontroller

The techniques and methodology for adaptive training of the ANN will be developed and shown here first using numerical simulations on examples with known analytic dynamic models. Different adaptation criteria will be considered. The results applied to a real heat exchanger test facility and its dynamic control will be shown in a later section.

3.1 Single Adaptation Criterion. We start with a simple example in which we track the behavior of a nonlinear dynamical system described by $\dot{y}+ay^3=x(t)$, where $x(t)$ is a forcing function taken to be $x(t)=\sin(t)$, and a is a parameter. We take $a=1$ for $t\in[0,25]$ and $a=4$ for $t\in(25,50]$. This represents a sudden change in system characteristics. A 2-5-1 ANN, i.e. one with an input layer with two input nodes, a hidden layer with five nodes and an output layer with one output node, is used to learn the behavior of the dynamical system. At $t=25$ the parameter a of the system is modified and the ANN is expected to adapt until it

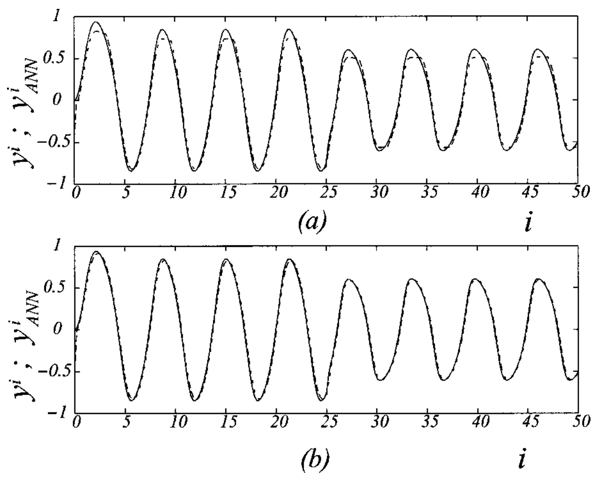

Fig. 3 Tracking of a dynamical system by an ANN; (*a*) adaptation for target error ⩾5 percent; (*b*) adaptation for target error ⩾1 percent; — numerical solution; -- ANN prediction

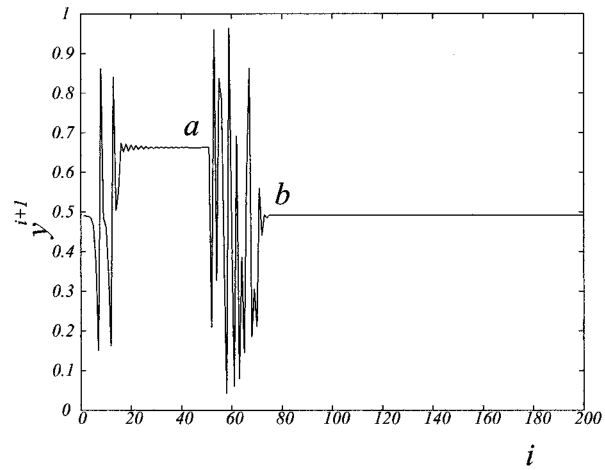

Fig. 4 Result of using a 2-4-1 ANN as an iterated map; *i* is the time index and y^{i+1} is the output

learns the new behavior of the system. The inputs to the ANN are y^i and x^i and the output is y^{i+1}, where i is a discrete time index.

Figures 3(*a*) and (*b*) show the results of tracking the output y^i compared with the numerical solution. In Fig. 3(*a*) the adaptation process is turned on for errors larger than five percent. It is seen that the overall behavior of the system is captured by the ANN, but there are still some discrepancies close to maximum values of the function. In Fig. 3(*b*) the ANN is adapted for errors larger than one percent. It is seen that the prediction is much closer to the numerical, but the program takes 20 percent longer to run. Thus, if we are performing an on-line adaptation there is a compromise between the error obtained and the length of the adaptation period.

3.2 Two Adaptation Criteria. We now examine the adaptation of ANNs using two criteria: one for accuracy in prediction and the other for stability. In this example we train a 2-4-1 neural network to learn the fixed point of the differential equation $\dot{y}+y=x^2$, where x^2 is a constant, and $y(0)$ is the same constant. This can be implemented with an ANN by providing only one set of values as the training data, i.e., inputs $y^i=0.49$, $x^i=0.7$ and output $y^{i+1}=0.49$. First we train the ANN for reduction of target error, and once this is less than 10^{-3}, we train it for stability.

From the stability perspective, we view the ANN as an iterated map, i.e., we supply the input values x^i and y^i and we obtain an output. This output becomes the input for the next iteration of the map. The value of x^i remains constant and the values of y^i iterate. The spectral radius of the Jacobian matrix of the map, r, is calculated to determine the stability.

We first train the ANN to make sure that $r>1$ with a target error less than 10^{-3}, and then we use the ANN as a dynamical system. As we expect, the system is unstable. In order to stabilize it at the correct fixed point, we modify the weights and biases of the ANN until r is sufficiently less than unity (we chose $r<0.9$ as a sufficiency criterion). We use a gradient descent method to modify the weights and biases of the ANN. As the target error might increase due to the fact that we are training in the direction of decreasing r, we need to retrain the ANN to reduce the target error again. Thus there is an alternating process of training with respect to the two different criteria until we obtain the desired value of the target error with $r<1$. Figure 4 shows the behavior of the dynamical system during this training process. The parameters of the ANN chosen make $r=4.7$ so that it is unstable to the iterative process. The system goes from the $y^i=0.49$ at $i=0$ for which the error was zero to the point a at $i=50$. This fixed point is stable with $r<1$, but is not the state that is desired. So we turn on the adaptation routine for the reduction of r to below unity along with reduction of error to bring the system back to point b where $y^i=0.49$. This occurs at about $i=77$. Thus it takes about 27 iterations for the system to stabilize at the desired fixed point.

There is a need for a back-up controller that will keep the system close to the set point when either the controller or the model of the plant is going through the adaptation process with respect to any of the chosen criteria. The process described in this section can also be used to modify the parameters (biases and weights) of the ANN controller with respect to several adaptation criteria.

3.3 Adaptation Criteria With Optimization. We now develop a third example showing the use of adaptive rules for driving a dynamical system composed by an ANN to a desired fixed point. We train an ANN with the function $y=1/x$ with $x\in[0.1,10]$. Each point of this curve is a fixed point of the ANN. The inputs of the ANN are y^i and x^i and the output is y^{i+1}. We select an initial condition within the given range of the variables. We check the stability of the system and the target error, but we want at the same time to drive the system to the maximum of the unrelated function $z=x(1-x)y(1-y)$. For this purpose we apply a gradient ascend method to modify the current values of x^i and y^i so that the dynamical system maximizes z. Figure 5 shows the behavior of the system during this process in (x,y,z) space. It moves from the initial condition along the given curve until it finds the maximum of the function z. Figure 6 shows the values of

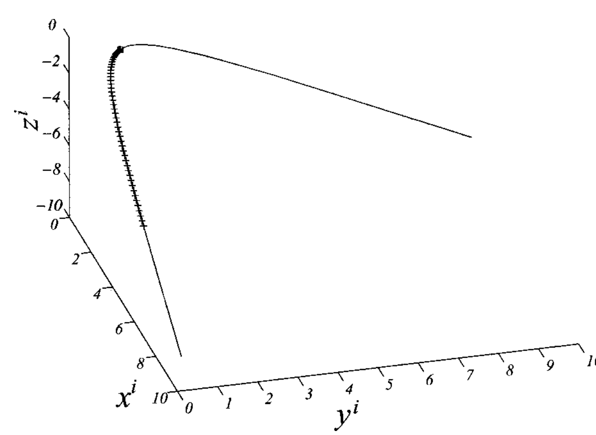

Fig. 5 Simultaneous optimization criteria; training curve is continuous line, path of dynamical system is shown with +

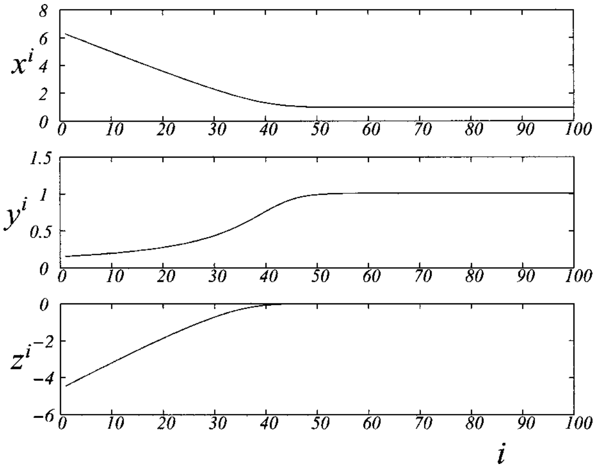

Fig. 6 *x*, *y*, and *z* versus discrete time index

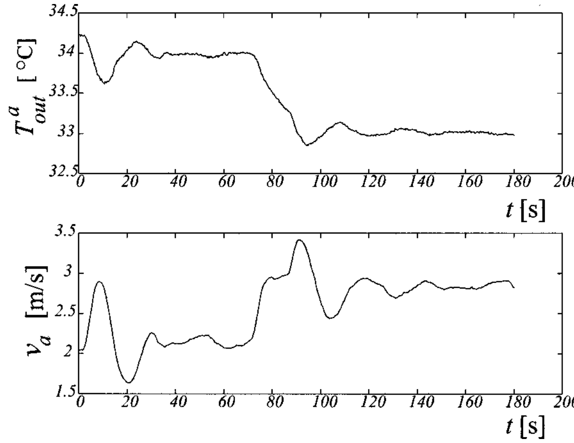

Fig. 8 Response to change in the T^a_{out} set point

x, y, and z at each iteration i. It is observed that since the spectral radius of the system was kept below unity, the maximum value of z is also a stable fixed point of the system.

4 Experimental Verification

We will now use the ANN training technique described above to control the exit air temperature of a heat exchanger. The experimental setup consists of a variable speed wind tunnel facility, shown in Fig. 7, with a water-to-air fin-tube heat exchanger as described by Zhao [15]. 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 blower that is controlled by a variable speed drive that can be operated manually or automatically from a personal computer. The air speed can be controlled within a certain range and is measured using a Pitot tube located upstream of the heat exchanger. The calibration of the air flow measurements was performed using average air velocities based on ASHRAE test codes. A single-point temperature measurement is used upstream of the heat exchanger and five thermocouples connected in parallel are used to obtain the T^a_{out} measurement. Information about inlet and outlet temperatures of both the air and water side, T^a_{in} and T^w_{in} respectively, the mass flow rate of water, $\dot{m}_w$, the air speed, v_a, and the time t at which the measurements were taken are sent to the PC that also serves as a controller. T^w_{in} is varied by using a heater with a PID-controlled electrical resistance. $\dot{m}_w$ is modified by an electronic valve so that the percentage of opening can be controlled as desired from the PC. The data acquisition board used can obtain measurements of up to 16 different channels, simultaneously. LabVIEW is used to acquire and send data to the experimental system and a program written in C interfaces with it to perform the desired control action.

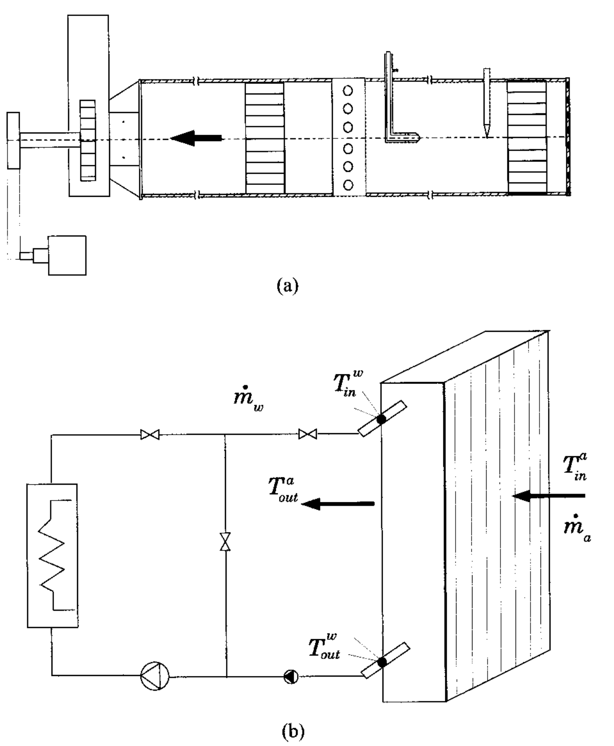

Fig. 7 Schematic of test facility: (*a*) wind tunnel; (*b*) heat exchanger connections

4.1 Change in the Set Point. The first test corresponds to a sudden change in the set point of T^a_{out}. Figure 8 shows a typical result of this experiment. The curve on the top shows the values of T^a_{out} and that on the bottom shows the values of the control variable v_a. The experiment consists on turning on the controller at an outlet air temperature close to 34°C. The volumetric flow rate of water in the system was kept constant at 2.71×10^{-4} m^3/s. If the adaptation criteria are not matched, i.e., stability and target error, then the controller starts the adaptation process to let a PID controller keep the physical plant as close as possible to the set point temperature until the adaptation criteria are satisfied. It is possible to see that, during approximately the first 30 seconds of the test, the controller is adapting and then it stabilizes the plant at the desired set point temperature. At $t=70$ s, we change the set point to 33°C. The controller detects an abrupt change in target error and starts another adaptation process. During this adaptation period, the PID controller takes over again and tries to keep the system close to the set point. At approximately $t=90$ s the controller regains control of the system and stabilizes it at the new set point. It is observed that v_a increases by approximately 50 percent.

4.2 Disturbance Rejection. The response of the controller to four different kinds of disturbances were determined.

(a) Water-Side Disturbance. The testing procedure is similar to the case of change in the set point. We turn on the controller and it adapts until the adaptation criteria are matched. The initial oscillations are mainly due to the action of a PID controller that controls the system while the neurocontroller adapts. It reacts to an arbitrary initial condition of the system that might not be exactly at the set point temperature. The neurocontroller then keeps the system close to $T^a_{\mathrm{out}}=34$°C, at which point we apply a distur-

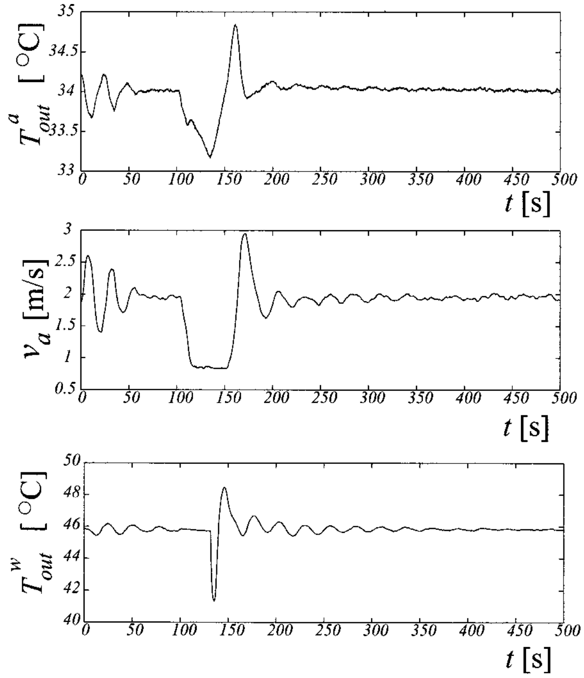

Fig. 9 Response to water-side disturbance

bance which consists of shutting off the water. Figure 9 shows the results of this experiment. The first 50 s is under the action of PID control, after which the neurocontroller takes over. At $t=100$ s we shut the water flow rate for a period of 30 s. The neurocontroller works until $t=110$ s at which point it hands the control action to PID while it is itself adapting. At $t=130$ s the water flow resumes. Meanwhile, the PID has tried to keep the reference temperature by reducing v_a to its minimum possible value but is unable to maintain T^a_{out} without the water flow. Adaptation of the neurocontroller is complete around $t=170$ s after which it takes over the control action. The graph also shows the water outlet temperature T^w_{out} during the same period. Between $t=100$ s and $t=130$ s there is no water flow so that the water outlet temperature remains constant. When water flow is resumed the cold water that was stagnant inside the HX flows past the thermocouple followed by the hot water that was stagnant in the heater; the resulting blip in T^w_{out} can be seen. The temperature oscillations are due to these portions of cold and hot water repeatedly passing by the thermocouple while circulating within the closed loop. It is observed that v_a has a similar oscillatory behavior.

(b) Air-Side Disturbance. We now perform perhaps the most difficult test for the controller by reducing the inlet air area of the wind tunnel representing a structural change in the thermal system. We do this in two ways, once gradually and then suddenly.

Figure 10 shows the results of the gradual reduction. The first 30 s is under PID control, and the neurocontroller gains control of the system at that point. From $t=100$ s until $t=220$ s we gradually block the inlet area until there is only one-half of the initial area left. As this happens, the neurocontroller increases v_a to keep the system at 34°C. There is a point at approximately $t=190$ s where the ANN model is not able to characterize the system and an adaptation process begins; the neurocontroller adapts until about $t=260$ s. After it has learned, the new relation between T^a_{out} and v_a takes over the control action to stabilize the system. It is observed that there are some oscillations of the temperature between $t=330$ s and $t=390$ s but T^a_{out} finally settles down to the set point.

To further test the adaptive ability of the controller, the previous experiment is repeated but with suddenly blocking one-half the inlet air area. We let the controller keep the system stable at $T^a_{\mathrm{out}}=34$°C and then block the inlet. The controller adapts until it is able to return the system to the same outlet air temperature. Figure 11 shows the results obtained for this test. For the first 50 s the controller adapts until it learns the behavior of the system and then it keeps it stable at 34°C. At $t=150$ s, the inlet area is blocked and we let the controller adapt until it learns the new characteristics of the system. It is seen that v_a increases approximately 50 percent. Finally at about $t=240$ s, the neurocontroller regains the control of the plant and stabilizes the system at the set point.

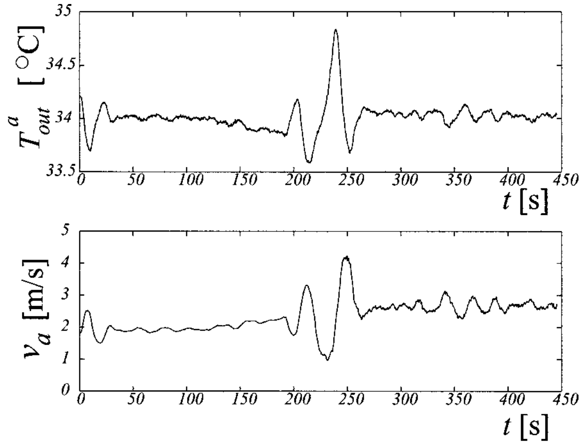

Fig. 10 Response to air-side disturbance; gradual reduction of the inlet air area

4.3 Energy Consumption. In order to minimize the energy consumption of the system, the main components that consume energy in the experimental facility need to be identified, and they are the hydraulic pump, the fan and the electric heater. Measurements of the voltage and current for these three components were made and the amount of energy consumed by each one of them could be determined. Different operating points of $\dot{m}_w$ and $\dot{m}_a$ were chosen for taking the measurements and the results indicated that the electric heater was the thermal component that consumed the most energy. Thus, we use the measurements taken from this component to develop a surface with $E=E(\dot{m}_w,\dot{m}_a)$, where E is the power consumed. Figure 12 shows the corresponding surface. As expected, the lower $\dot{m}_w$ and $\dot{m}_a$, the lower is the use of energy.

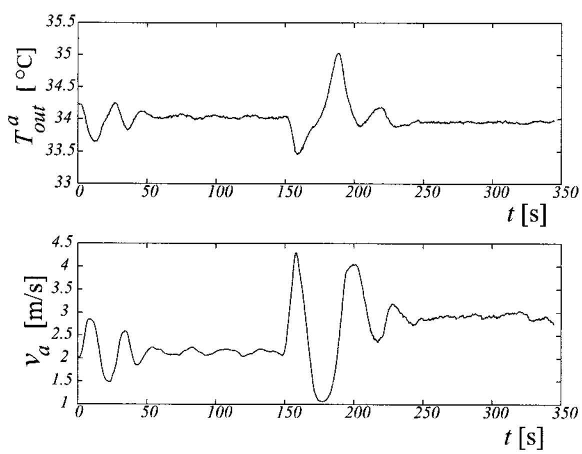

Fig. 11 Response to air-side disturbance; sudden reduction of the inlet air area

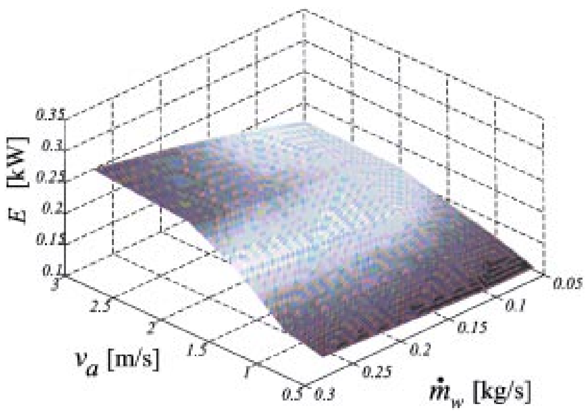

Fig. 12 Energy consumption surface $E(v_a, \dot{m}_w)$

We use this surface now to find the value of the energy for each sampled measurement during the operation of the system and to determine the direction of minimal use of energy. We let the controller drive the system in this direction. If the controller senses that the system is behaving in a different way, it will adapt to the new characteristics of the system.

In addition to the two previous adaptation criteria for the weights and biases of the ANNs, i.e., low target error and stable operation, we added the third which is the minimization of energy consumption. We let the controller stabilize the system at $T^a_{\mathrm{out}} = 34°\mathrm{C}$ and then turn on the training using the third criterion. Figure 13 shows the results obtained. The controller is supposed to keep the system stable at the same T^a_{out}. The minimization of energy routine reduces the $\dot{m}_w$ so that the controller has to reduce $\dot{m}_a$. The disturbance is not strong enough to make the controller detect a change in the system characteristics so no adaptation is needed, and the system is successfully kept at the set point.

It is noted that in the present study, there is essentially one controlled parameter (exit air temperature) and one controlling parameter (air flow), and several other operating parameters remain constant. This is however not a limitation of the adaptive neurocontroller strategy. As already shown in the case where a disturbance in the water flow is introduced (Fig. 9), the additional training due to the changed water flow and its effect on the exit air temperature provides the needed modulation of the neurocontroller. However, it is true that for general multiple controlling and controlled-parameter problems, the control strategy does become more complex and requires further study.

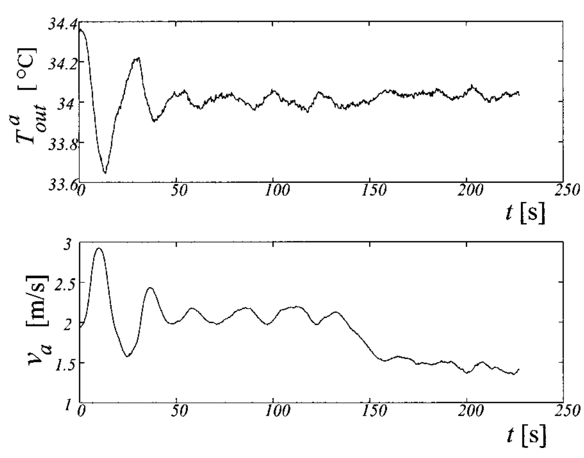

Fig. 13 Application of energy minimization routine. $\dot{m}_w$ is reduced to consume less energy and as a consequence, $\dot{m}_a$ is also reduced.

5 Conclusions

It has been previously shown that ANNs are a powerful technique to model and control nonlinear systems. They can be trained to give small errors in prediction and a stable closed-loop feedback control operation. However, one of the main advantages of ANNs is that they are easy to adapt such that their parameters can be modified on-line. We have shown how this can be done in also minimizing some other index, such as energy consumption, at the same time. The neurocontroller was able to control the experimental facility and adapt to its new conditions for disturbances in the air and water flow rates. It was also able to learn and control the plant behavior for a change in the set point of the temperature. The methodology is fairly general; the same procedure can be used, for example, for the adaptive and stable control of other thermal systems while at the same time minimizing the energy used. The results of this study suggest that ANNs are useful for the control of thermal systems that may change over time.

Acknowledgments

We gratefully acknowledge the support of Mr. D. K. Dorini of BRDG-TNDR for this and related projects in the Hydronics Laboratory. G. D. also thanks the Organization of American States for a PRA Fellowship.

Nomenclature

a = parameter of the analytical model
E = power consumed [kW]
F = filter for control scheme
I = integral control
i = discrete time index
$\dot{m}$ = mass flow rate [kg/s]
r = spectral radius of Jacobian matrix
T = temperature [°C]
T_{ref} = reference temperature [°C]
t = time [s]
u = control action
v = air speed [m/s]
x = control variable
y = controlled variable
z = optimization variable

Subscripts and Superscripts

a = air side
in = inlet
out = outlet
w = water side

References

[1] Sen, M., and Yang, K. T., 2000, ''Applications of Artificial Neural Networks and Genetic Algorithms in Thermal Engineering,'' *CRC Handbook of Thermal Engineering*, section 4.24, F. Kreith, ed., pp. 620–661.
[2] Díaz, G., Sen, M., Yang, K. T., and McClain, R. L., 1999, ''Simulation of Heat Exchanger Performance by Artificial Neural Networks,'' HVAC&R Research Journal, **5**, No. 3, pp. 195–208.
[3] Kays, W. M., and London, A. L., 1984, *Compact Heat Exchangers*, 3rd ed., McGraw-Hill, New York.
[4] Sundén, B., and Faghri, M., (eds.), 1998, *Computer Simulations in Compact Heat Exchangers*, Computational Mechanics Publications, Boston, MA.
[5] Díaz, G., Sen, M., Yang, K. T., and McClain, R. L., 2001, ''Dynamic Prediction and Control of Heat Exchangers Using Artificial Neural Networks,'' International Journal of Heat and Mass Transfer, **44**, pp. 1671–1679.
[6] Marwah, M., Li, Y., and Mahajan, R. L., 1996, ''Integrated Neural Network Modeling for Electronic Manufacturing,'' J. Electron. Manuf., **6**, No. 2, pp. 79–91.
[7] Blazina, A., and Bolf, N., 1997, ''Neural Network-Based Feedforward Control of Two-Stage Heat Exchange Process,'' *Proceedings of the IEEE International Conference on Systems, Man and Cybernetics*, **1**, pp. 25–29.
[8] Ayoubi. M. 1997, ''Dynamic Multi-Layer Perceptron Networks: Application to the Nonlinear Identification and Predictive Control of a Heat Exchanger,''

Applications of Neural Adaptive Control Technology, World Scientific Series in Robotics and Intelligent Systems, **17**, pp. 205–230.
[9] Nahas, E. P., Henson, M. A., and Seborg, D. E., 1992, ''Nonlinear Internal Model Control Strategy for Neural Network Models,'' Comput. Chem. Eng., **16**, No. 12, pp. 1039–1057.
[10] Chen, C. T., Hwu, J., and Chang, W. D., 1999, ''Nonlinear Process Control Based on Using an Adaptive Single Neuron,'' J. Chin. Inst. Chem. Eng., **30**, No. 2, pp. 141–149.
[11] Haykin, S., 1994, *Neural Networks, A Comprehensive Foundation*, Macmillan College Publ. Co., New York.
[12] Díaz, G., Sen, M., Yang, K. T., and McClain, R. L., 2001, ''Stabilization of Thermal Neurocontrollers,'' International Journal of Heat and Mass Transfer, in press.
[13] Hunt, K. J., Sbarbaro, D., Zbikowski, R., and Gawthrop, P. J., 1992, ''Neural Networks for Control Systems—A Survey,'' Automatica, **28**, No. 6, pp. 1083–1112.
[14] Landau, I. D., Lozano, R., and M'Saad, M., 1998, *Adaptive Control*, Springer-Verlag, London.
[15] Zhao, X., 1995, ''Performance of a Single-Row Heat Exchanger at Low In-Tube Flow Rates,'' M.S. thesis, Department of Aerospace and Mechanical Engineering, University of Notre Dame, IN.