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Implementation of A Model Reference Adaptive Control System Using Neural Network to Control A Fast Breeder Reactor Steam Evaporator

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IMPLEMENTATION OF A MODEL REFERENCE ADAPTIVE CONTROL SYSTEM USING NEURAL NETWORK TO CONTROL A FAST BREEDER REACTOR EVAPORATOR

D. Ugolini* , S. Yoshikawa**, and A. Endou**

ABSTRACT

This paper discusses the development of an indirect model reference adaptive control (MRAC) system, using the artificial neural network (ANN) technique, and its implementation to control the outlet steam temperature of a sodium to water helical-coil once-through evaporator. The ANN technique is applied in the identification process and in the control process of the indirect MRAC system. The evaporator is simulated with a nonlinear dynamic modular model representing a superheated cycle with three regions, subcooled, saturated, and superheated, and moving boundaries.

The emphasis is placed on demonstrating the efficacy of the indirect MRAC system in the control of the outlet steam temperature of the evaporator model, and on showing the important function covered by the ANN technique, whose adaptation and learning capabilities, contribute to improve the performance of the control action of the indirect MRAC system.

The implementation of the ANN technique in the indirect MRAC system generates a strong control system. An important characteristic of this control system is that it relays only on some selected input variables and on the output variables of the evaporator model. These are the variables that can be actually measured or calculated in a real environment. Therefore, the internal variables, which are needed to develop the model, but that can be hardly measured or calculated in a real environment, are not utilized during the control action performed by the indirect MRAC system.

The results obtained applying the indirect MRAC system to control the evaporator model are quite remarkable. The outlet temperature of the steam is almost perfectly kept close to its desired set point, when the evaporator model is forced to depart from steady state conditions, either due to the variation of some input variables or due to the alteration of some of its internal parameters.

The results also show the importance of the role played by the ANN technique in the overall control action of the indirect MRAC system. The connecting weights and the biases of the nodes of the ANN self adjust to follow the modifications which may occur in the characteristic of the evaporator model during a transient. The efficiency and the accuracy of the control action highly depends on the on line identification process of the ANN, which is responsible for the upgrade of the connecting weights and of the biases of the ANN nodes.

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ニューラルネットワークを用いたモデル適応制御手法の高速増殖炉用蒸気発生器制御への応用

Ugolini, Daniele*, 吉川 信治**, 遠藤 昭**

要旨

本報告書は、人工的に構築されたニューラルネットワーク(ANN:Artificial Neural Network)を用いた間接的モデル適応制御(MRAC)システムと、これの、ヘリカルコイル型のナトリウム－水伝熱管を有する貫流型蒸気発生器の出口蒸気温度の制御への応用について議論する。 このシステムでは、ニューラルネットワークは対象の特性の同定を行なう部分と制御を行なう部分の２ヵ所に組込まれている。蒸気発生器は非線形の動的なモジュラー型モデルで模擬している。このモデルでは伝熱部が水／蒸気側の状態－－サブクール水、飽和水／蒸気、過熱蒸気－－によって３領域に分割されて計算され、各領域間の境界は動的に変化する。

本報告書の要点は、間接的モデル適応制御の蒸気発生器モデルの出口蒸気温度制御への有効性を示したことと、この手法においてニューラルネットワークで実現されている重要な機能を示したことである。ニューラルネットワークの適応と学習の能力はこの間接的モデル適応制御の制御性能の改善に貢献している。

間接的モデル適応制御へニューラルネットワークを組込んだことにより、強力な制御システムが実現した。この制御システムの重要な特徴は、これが蒸気発生器モデルの入力変数と出力変数の全てを必要とはしないということである。本研究においては、これらの変数として、実機の環境で計測あるいは算出可能なものだけを選択した。従って、内部の変数は、モデルの開発には必要であるが実機の環境では計測や算出がほぼ不可能であるので、この間接的モデル適応制御システムには用いられていない。

この間接的モデル適応制御手法を蒸気発生器モデルへ適応した結果は極めて良好であった。蒸気発生器モデルを、境界条件の変化や内部パラメータの変化によって、強制的に平衡状態から離脱させた場合でも、出口蒸気温度はほぼ完全に設定値に保たれた。

また、この結果から間接的モデル適応制御システムの全体の制御動作においてニューラルネットワークの果す役割の重要性が示された。ニューラルネットワークの各ノードの結合係数や偏差は、蒸気発生器モデルの過渡変化中に起こり得る特性の変化に追従するために自ら変化する。本システムの制御動作の効率と精度は、この結合係数や偏差の自動調整を担うニューラルネットワークのオンラインでの特性同定プロセスに強く依存している。

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1. INTRODUCTION

System identification[1] and control methods[2] for linear systems based on mathematical system theory are well established. The most widely used technique is the model reference adaptive control (MRAC) system[3]. Similar studies for nonlinear systems have been almost neglected mainly for their intrinsic complexity and for the lack of proper mathematical tools.

The artificial neural network (ANN) technique[4], an artificial intelligence method, based mostly on experimental techniques offers the possibility to circumvent such obstacles. The association of the ANN algorithm with the MRAC system provides a powerful tool for controlling nonlinear systems.

This paper presents the implementation of an indirect MRAC system using the ANN technique to control the outlet steam temperature of a sodium to water evaporator. In the next section a brief description of the characteristics of the nonlinear dynamic modular model of the fast breeder reactor evaporator is given. In section 3, the direct and the indirect MRAC system are described. The ANN technique and its utilization in the identification process and in the control process of the indirect MRAC system are described in section 4 and 5. In section 6, the operation procedure of the indirect MRAC system is exposed. The results obtained applying the indirect MRAC system in the control of the evaporator model and the importance covered by the ANN technique are discussed in section 7. Some conclusive remarks are presented in section 8.

2. DESCRIPTION AND MATHEMATICAL FORMULATION OF THE EVAPORATOR MODEL

The fast breeder reactor evaporator modelled in this study is a once-through helical-coil type evaporator. It is a vertical, sodium to water, counterflow shell and tube heat exchanger. The boundaries of the model are defined by the inlet and outlet nozzles of the liquid sodium and of the feedwater. The feedwater enters the evaporator in the subcooled state. The steam leaves the evaporator in the superheated state.

The model, shown in Figure 1, consists of three sections representing, the sodium, the feedwater, and the metal which separates the sodium from the feedwater. Each section is divided into three regions, (1) the subcooled region, (2) the saturated region, and (3) the superheated region, according to the state of the water/steam mixture. The regions have moving boundaries, whose locations is denoted, in the model, by the state variables L_{sc}, and

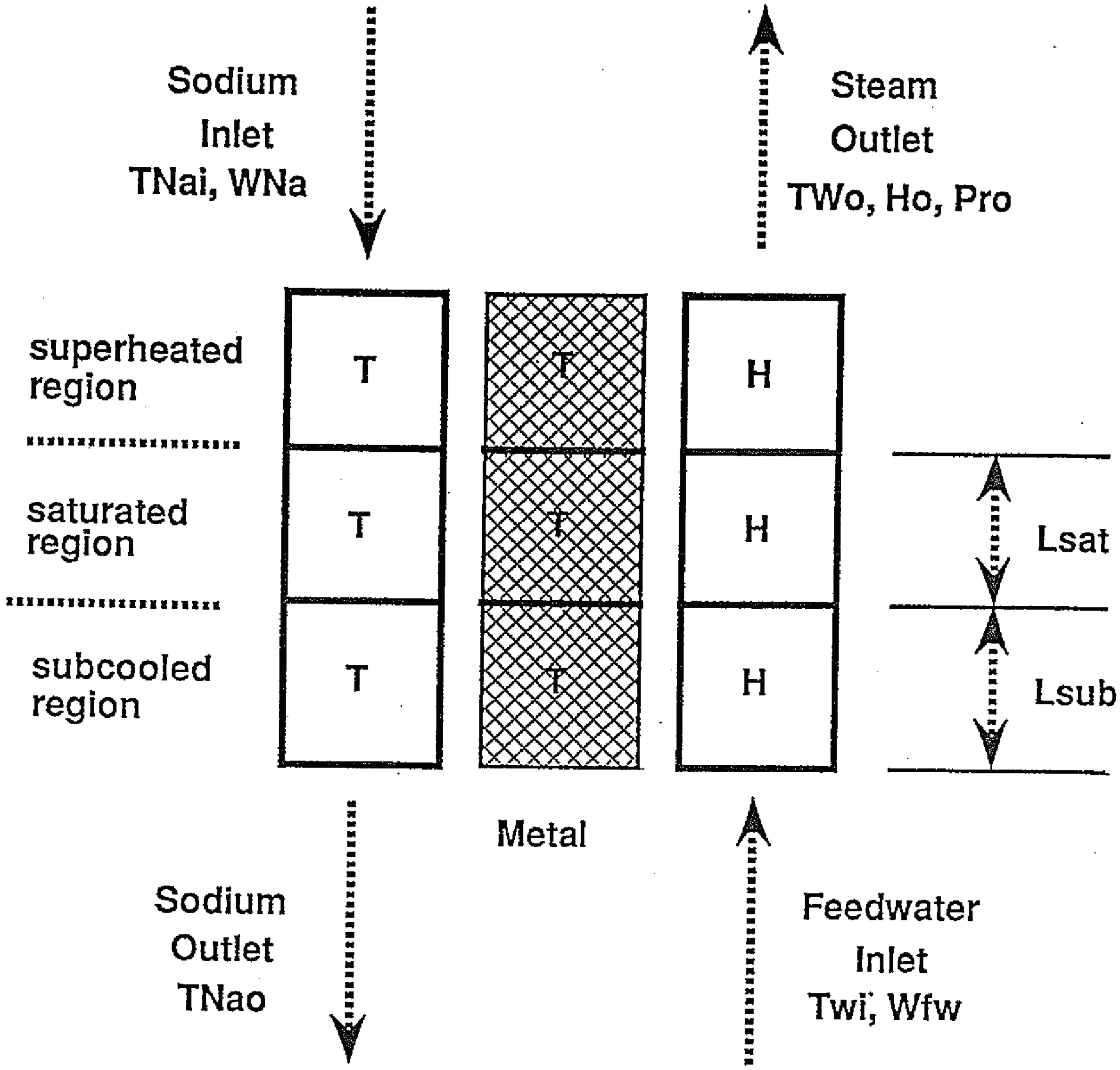

Figure 1.. Model diagram of the evaporator.

L_{st}, that represent the length of the subcooled region, and the length of the saturated region respectively. The model equations have been derived from the energy and mass conservation fundamental equations using the method of control volumes.

The sodium section is described by the following three equations, which respectively define the subcooled region,

$$\frac{dT_{Na_{sc}}}{dt} = \frac{2\ W_{Na}\ (T_{Na_{sc}} - T_{Na_o})}{m_{Na}\ \dfrac{L_{sc}}{L}} - \frac{U_{ssc}\ (T_{Na_{sc}} - T_{M_{sc}})}{K_{Na_{sc}}\ m_{Na}} \quad , \tag{1}$$

the saturated region,

$$\frac{dT_{Na_{st}}}{dt} = \frac{W_{Na}\ (2\ T_{Na_{sh}} - 2\ T_{Na_{sc}} + T_{Na_o} - T_{Na_i})}{m_{Na}\ \dfrac{L_{st}}{L}} - \frac{U_{sst}\ (T_{Na_{st}} - T_{M_{st}})}{K_{Na_{st}}\ m_{Na}} \quad , \tag{2}$$

and the superheated region,

$$\frac{dT_{Na_{sh}}}{dt} = \frac{2\ W_{Na}\ (T_{Na_i} - T_{Na_{sh}})}{m_{Na}\ \dfrac{(L - L_{st} - L_{sc})}{L}} - \frac{U_{ssh}\ (T_{Na_{sh}} - T_{M_{sh}})}{K_{Na_{sh}}\ m_{Na}} \quad . \tag{3}$$

The metal section is described by the following three equations, which respectively define the subcooled region,

$$\frac{dT_{M_{sc}}}{dt} = \frac{U_{ssc}\ (T_{Na_{sc}} - T_{M_{sc}}) - U_{msc}\ (T_{M_{sc}} - T_{W_{sc}})}{K_M\ m_M} \quad , \tag{4}$$

the saturated region,

$$\frac{dT_{M_{st}}}{dt} = \frac{U_{sst}\ (T_{Na_{st}} - T_{M_{st}}) - U_{mst}\ (T_{M_{st}} - T_{W_{st}})}{K_M\ m_M} \quad , \tag{5}$$

and the superheated region,

$$\frac{dT_{M_{sh}}}{dt} = \frac{U_{ssh}\ (T_{Na_{sh}} - T_{M_{sh}}) - U_{msh}\ (T_{M_{sh}} - T_{W_{sh}})}{K_M\, m_M} \quad . \tag{6}$$

The feedwater region is described by the following six equations, which respectively define the subcooled region,

$$\rho_{sc}\,\frac{dH_{sc}}{dt} - \frac{dP}{dt} = \frac{[U_{ssc}\ (T_{Na_{sc}} - T_{M_{sc}})\ \frac{L_{sc}}{L}] + [W_{fw}\ (H_i - H_f)]}{A\ L_{sc}} \quad , \tag{7}$$

$$\rho_{sc}\,\frac{dL_{sc}}{dt} + L_{sc}\ (\frac{\partial\rho_{sc}}{\partial H_{sc}}\ \frac{dH_{sc}}{dt} + \frac{\partial\rho_{sc}}{\partial P}\ \frac{dP}{dt}) = 0 \quad , \tag{8}$$

the saturated region,

$$\rho_{st}\,\frac{dH_{st}}{dt} - \frac{dP}{dt} = \frac{[U_{sst}\ (T_{Na_{st}} - T_{M_{st}})\ \frac{L_{st}}{L}] + [W_{fw}\ (H_f - H_g)]}{A\ L_{st}} \quad , \tag{9}$$

$$\rho_{st}\,\frac{dL_{st}}{dt} + L_{st}\ (\frac{\partial\rho_{st}}{\partial H_{st}}\ \frac{dH_{st}}{dt} + \frac{\partial\rho_{st}}{\partial P}\ \frac{dP}{dt}) = 0 \quad , \tag{10}$$

and the superheated region,

$$\rho_{sh}\,\frac{dH_{sh}}{dt} - \frac{dP}{dt} =$$

$$\frac{[U_{ssh}\ (T_{Na_{sh}} - T_{M_{sh}})\ \frac{(L - L_{st} - L_{sc})}{L}] + [W_{fw}\ (H_g - H_o)]}{A\ (L - L_{sc} - L_{st})} \quad , \tag{11}$$

$$-\rho_{sh}\left(\frac{dL_{st}}{dt}+\frac{dL_{sc}}{dt}\right)+$$

$$(L-L_{sc}-L_{st})\left(\frac{\partial\rho_{sh}}{\partial H_{sh}}\frac{dH_{sh}}{dt}+\frac{\partial\rho_{sh}}{\partial P}\frac{dP}{dt}\right)=0\ . \tag{12}$$

The state variables that describe the evaporator model are,

T_{Nasc} = average sodium temperature of the subcooled region,
T_{Nast} = average sodium temperature of the saturated region,
T_{Nash} = average sodium temperature of the superheated region,
T_{Msc} = average metal temperature of the subcooled region,
T_{Mst} = average metal temperature of the saturated region,
T_{Msh} = average metal temperature of the superheated region,
H_{sc} = average enthalpy of the subcooled region,
H_{st} = average enthalpy of the saturated region,
H_{sh} = average enthalpy of the superheated region,
L_{sc} = length of the subcooled region,
L_{st} = length of the saturated region,
P = average steam pressure.

The input variables of the evaporator model are,

T_{Nai} = inlet sodium temperature,
W_{Na} = inlet sodium flow rate,
T_i = inlet feedwater temperature,
H_i = inlet feedwater enthalpy,
W_{fw} = feedwater flow rate.

The outlet variables calculated by the evaporator model are,

T_{Nao} = outlet sodium temperature,
H_o = outlet feedwater enthalpy,
T_{wo} = outlet steam temperature.

The internal variables that describe the evaporator model are,

U_{ssc} = sodium to metal heat transfer coefficient, subcooled region,
U_{sst} = sodium to metal heat transfer coefficient, saturated region,
U_{ssh} = sodium to metal heat transfer coefficient, superheated region,
U_{msc} = metal to water heat transfer coefficient, subcooled region,
U_{mst} = metal to water/steam heat transfer coefficient, saturated region,

U_{msh} = metal to steam heat transfer coefficient, superheated region,
$K_{Na,sc}$ = sodium specific heat, subcooled region,
$K_{Na,st}$ = sodium specific heat, saturated region,
$K_{Na,sh}$ = sodium specific heat, superheated region,
K_M = metal heat capacity,
$T_{W,sc}$ = average water temperature, subcooled region,
$T_{W,st}$ = average water/steam temperature, saturated region,
$T_{W,sh}$ = average steam temperature, superheated region,
ρ_{sc} = average water density, subcooled region,
ρ_{st} = average water/steam density, saturated region,
ρ_{sh} = average steam density, superheated region,
H_f = water saturation enthalpy,
H_g = steam saturation enthalpy,
L = total height of the evaporator,
m_{Na} = sodium mass,
m_M = metal mass,
A = average cross section of the water/steam channel.

The system of six nonlinear differential equations, representing the feedwater region, is solved using a decoupling procedure, which generates the following system, (shown in a matrix form),

$$\begin{bmatrix} \frac{dH_{sc}}{dt} \\ \frac{dH_{st}}{dt} \\ \frac{dH_{sh}}{dt} \\ \frac{dP}{dt} \\ \frac{dL_{sc}}{dt} \\ \frac{dL_{st}}{dt} \end{bmatrix} = \begin{bmatrix} \rho_{sc} & 0 & 0 & -1 & 0 & 0 \\ L_{sc}\frac{\partial\rho_{sc}}{\partial H_{sc}} & 0 & 0 & L_{sc}\frac{\partial\rho_{sc}}{\partial P} & \rho_{sc} & 0 \\ 0 & \rho_{st} & 0 & -1 & 0 & 0 \\ 0 & L_{st}\frac{\partial\rho_{st}}{\partial H_{st}} & 0 & L_{st}\frac{\partial\rho_{st}}{\partial P} & 0 & \rho_{st} \\ 0 & 0 & \rho_{sh} & -1 & 0 & 0 \\ 0 & 0 & \Delta L\frac{\partial\rho_{sh}}{\partial H_{sh}} & \Delta L\frac{\partial\rho_{sh}}{\partial P} & -\rho_{sh} & -\rho_{sh} \end{bmatrix}^{-1} \begin{bmatrix} B(7) \\ B(8) \\ B(9) \\ B(10) \\ B(11) \\ B(12) \end{bmatrix}, \quad (13)$$

with,

$$\Delta L = L - L_{sc} - L_{st} \ ,$$

and where the column matrix, B(), represents the right hand side of the related feedwater equations.

In order to facilitate the implementation of the indirect MRAC system, the nonlinear differential equations representing the evaporator model have been transformed in a system of nonlinear difference equations using a numerical difference to approximate the derivative term,

$$\frac{df(x)}{dt} \fallingdotseq \frac{f(x+dt)-f(x)}{dt} \quad . \tag{14}$$

Therefore, a differential equation,

$$\frac{dx}{dt} = g(x,t) + u(t) \quad , \tag{15}$$

is transformed in the following difference equation,

$$x(t+\Delta t) = [g(x,t) + u(t)]\,\Delta t + x(t) \quad . \tag{16}$$

The evaporator model utilizes the specifications of the evaporator of the Monju prototype fast breeder reactor.

3. MODEL REFERENCE ADAPTIVE CONTROL SYSTEM

There are several adaptive control techniques for linear and nonlinear systems[5] which provide a systematic approach for the on line adjustment of controller parameters that vary during normal operations. Adaptive control systems that make use of models for the attainment of the control action are defined as model reference adaptive control systems. The MRAC technique is relatively easy to apply and, as it has been shown in several cases, it is capable to provide quite good performances.

In order to avoid confusion in the terminology, the model or the system that we want to control is going to be defined as plant. In this specific study the plant represents the evaporator model.

The objective of an MRAC system is, to minimize the norm of the difference between the output of a plant, in this study, the outlet steam temperature of the evaporator model, y_p, and the desired prescribed output, y_m, determined by a reference model,

$$|y_p(t) - y_m(t)| \leq \epsilon \ , \tag{17}$$

The above expression must be satisfied for any time, t, and for any specified constant $\varepsilon \geq 0$.

There are two classes of MRAC systems, the direct or explicit MRAC system and the indirect or implicit MRAC system.

In the indirect MRAC system[5], the control process is structured in two distinct processes the identification one and the control one. The purpose of the identification process is to generate a model of the plant, defined as the identification model, which must be capable to reproduce the behavior of the plant. Therefore, providing the same input to the plant and to the identification model, the identification model and the plant should generate the same output. It is the output of the identification model, y_{mi}, rather than the output of the plant, y_p, that is used in the control process of the indirect MRAC system. The control action is attained minimizing the norm of the difference between the output of the identification process, y_{mi}, and the desired prescribed output, y_m, determined by the reference model,

$$|y_{mi}(t) - y_m(t)| \leq \epsilon \ . \tag{18}$$

The result of expression (18) is also used to upgrade the dynamic parameters of the control process and of the identification process.

In the direct MRAC system, the parameters of the control process are directly adjusted during the control action, since the controller is applied directly on the plant. Therefore, it is not necessary to develop an identification model of the plant.

Even if the structure of direct MRAC systems is clearly simpler and more straight-forward than the indirect ones, the application of direct MRAC systems is limited to nonlinear plants whose dynamical parameters are all known. Unfortunately, this is not always true, and, in reality, most of the time, some of the parameters of the plant are unknown. In this condition it is necessary to use an indirect MRAC system.

In this study, we use an indirect MRAC system, whose process of identification of the plant and whose process of control of the plant are constructed using the ANN technique.

4. PLANT IDENTIFICATION USING NEURAL NETWORK

The process of identification of the plant is obtained using a series-parallel method[4], shown in Figure 2, with the application of the ANN technique.

The ANN[6], used in this study and shown in Figure 3, is a feedforward multi-layer neural network consisting of three neuron or node layers, namely the input, the hidden, and the output one. The number of nodes of each layer varies according to the characteristic of the problem being studied. A connecting weight and a bias are associated to each node link. These two parameters are both adjustable. The transfer function used in the nodes of the input and of the hidden layer is the hypertangent sigmoid or tan-sigmoid which maps an input to the node from the interval $(-\infty,+\infty)$ into the interval $(-1,1)$,

$$F = \frac{1-e^{-x}}{1+e^{-x}} = \tanh\left[\frac{x}{2}\right] \quad . \tag{19}$$

The linear activation transfer function is used in the nodes of the output layer. This function simply transfers the input to the node to the output of the node, without effecting any change, except for upgrading the its bias.

The process of identification of the plant, is obtained training the ANN (i.e. upgrading the connecting weights of each node), with a back-propagation algorithm, with momentum, which helps to overcome local-minima problems, and adaptive learning rate[5], which decreases the training time, shown in the following expression,

$$w_{ij}^{m}(t+1) = w_{ij}^{m}(t) + \eta\, \delta_{i}^{m} X_{j}^{m-1} + \mu\,[w_{ij}^{m}(t) - w_{ij}^{m}(t-1)] \quad . \tag{20}$$

where,

w_{ij}^{m} = connecting weight from the ith node of layer (m−1) to the jth node of layer m,

η = learning rate gain,

μ = momentum gain,

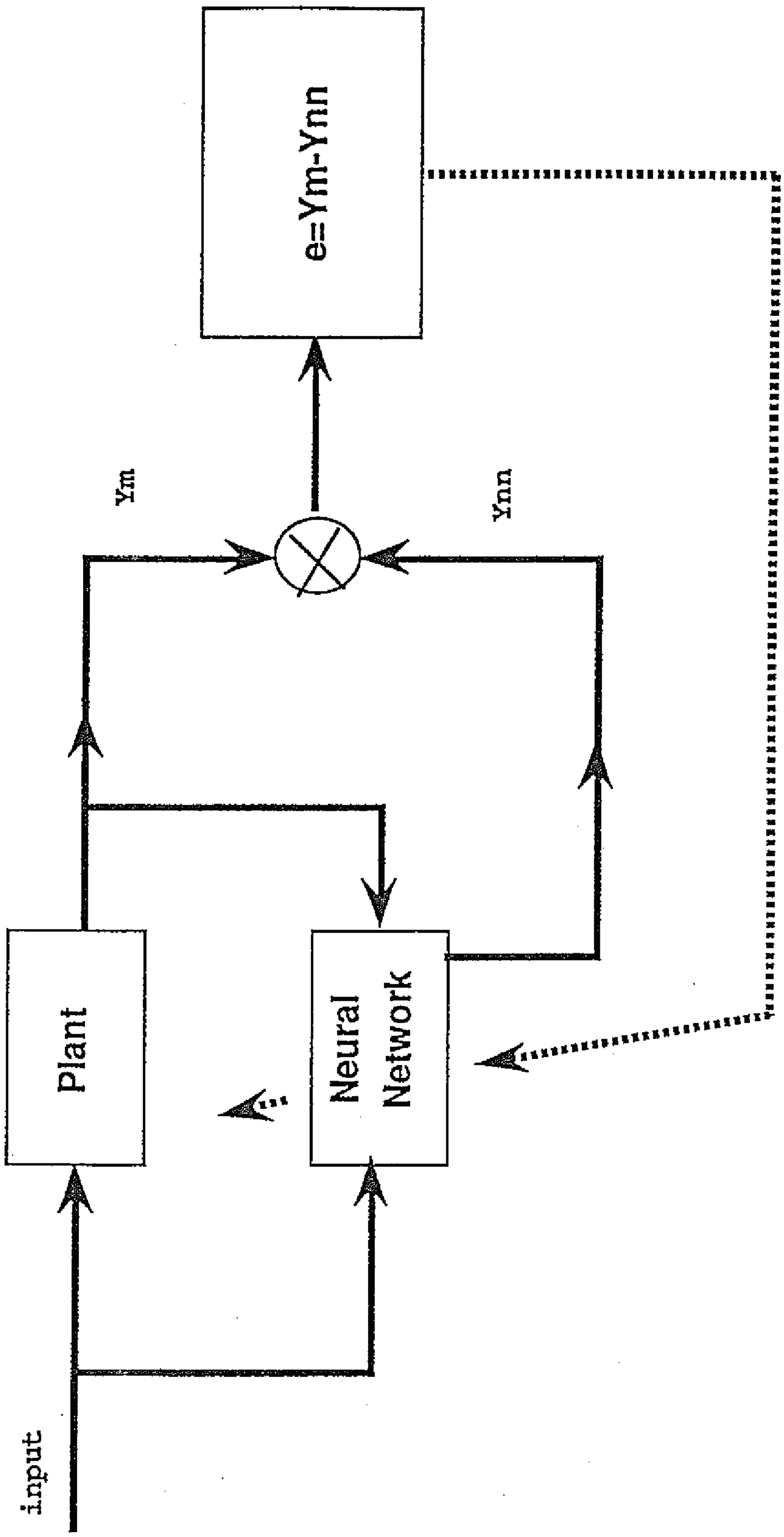

Figure 2. Series-Parallel model identification using neural network.

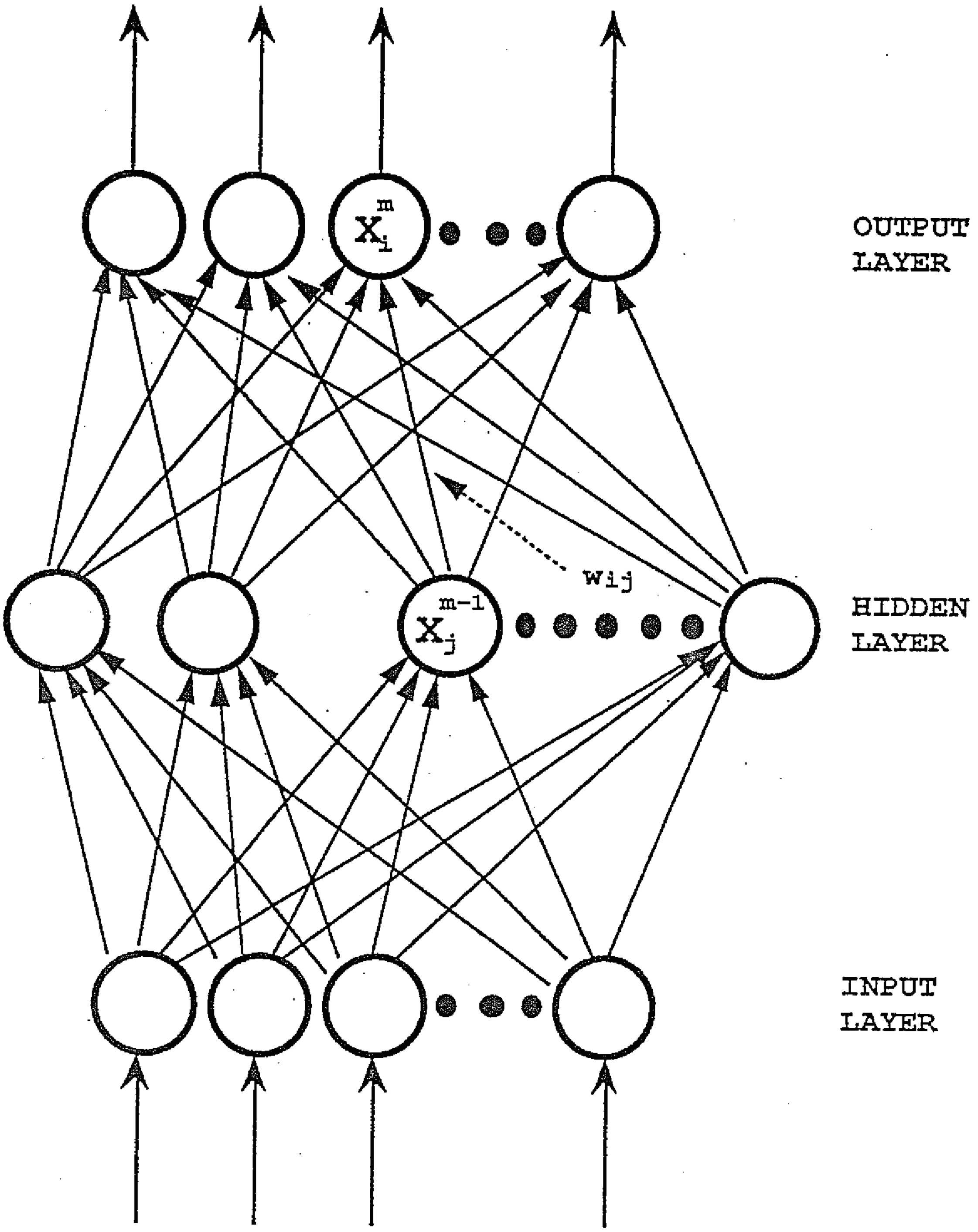

Figure 3. Diagram of a three layer feedforward artificial neural network

δ_i^m = generalized delta value (error of the ith node of layer m,

X_i^{m-1} = output of the jth node of the (m-1) layer, calculated using the proper transfer function.

The identification process is performed with an iterative procedure. At the beginning of each iteration, (a) a random perturbation is introduced in the plant, (b) the output variables of the plant, resulting from such perturbation are used as input variables for the ANN, (c) the connecting weights and the bias of each node of the ANN are adjusted, using the back-propagation algorithm, minimizing the norm of the difference between the output variables of the ANN and the corresponding output variables generated by the plant with the gradient descent method[7].
A successful training is achieved when the sum of the square of the errors (SSE) between the ANN output and the plant output is reduced to an acceptable level.

Initially, the ANN identification process is performed off-line, starting with the plant at steady state or stationary conditions. Then, the ANN identification process is kept active during the control action of the indirect MRAC system.

In this study, the input variables to the identification ANN are the outlet steam pressure, the outlet steam enthalpy, the average between the inlet and the outlet sodium temperature, the outlet steam temperature, and the feedwater flow rate. The feedwater flow rate is also the control variable. The output variables calculated by the identification ANN, that correspond to the output variables calculated by the plant, are the outlet steam pressure, the outlet steam enthalpy, the outlet sodium temperature, and the outlet steam temperature. The choice of the input and of the output variables has been based on the fact that they can be actually measured and calculated in a real environment. The internal variable used to develop the mathematical model of the evaporator, but that can hardly be measured or calculated in a real environment, are not used during the performance of the control action of the indirect MRAC system.

An example of the variation of the adaptive learning rate of the ANN and of the variation of the SSE during a typical training procedure is shown in Figure 4.

As previously stated, the same procedure is performed on line, in order to adjust the parameters of the ANN control process and of the ANN identification process.

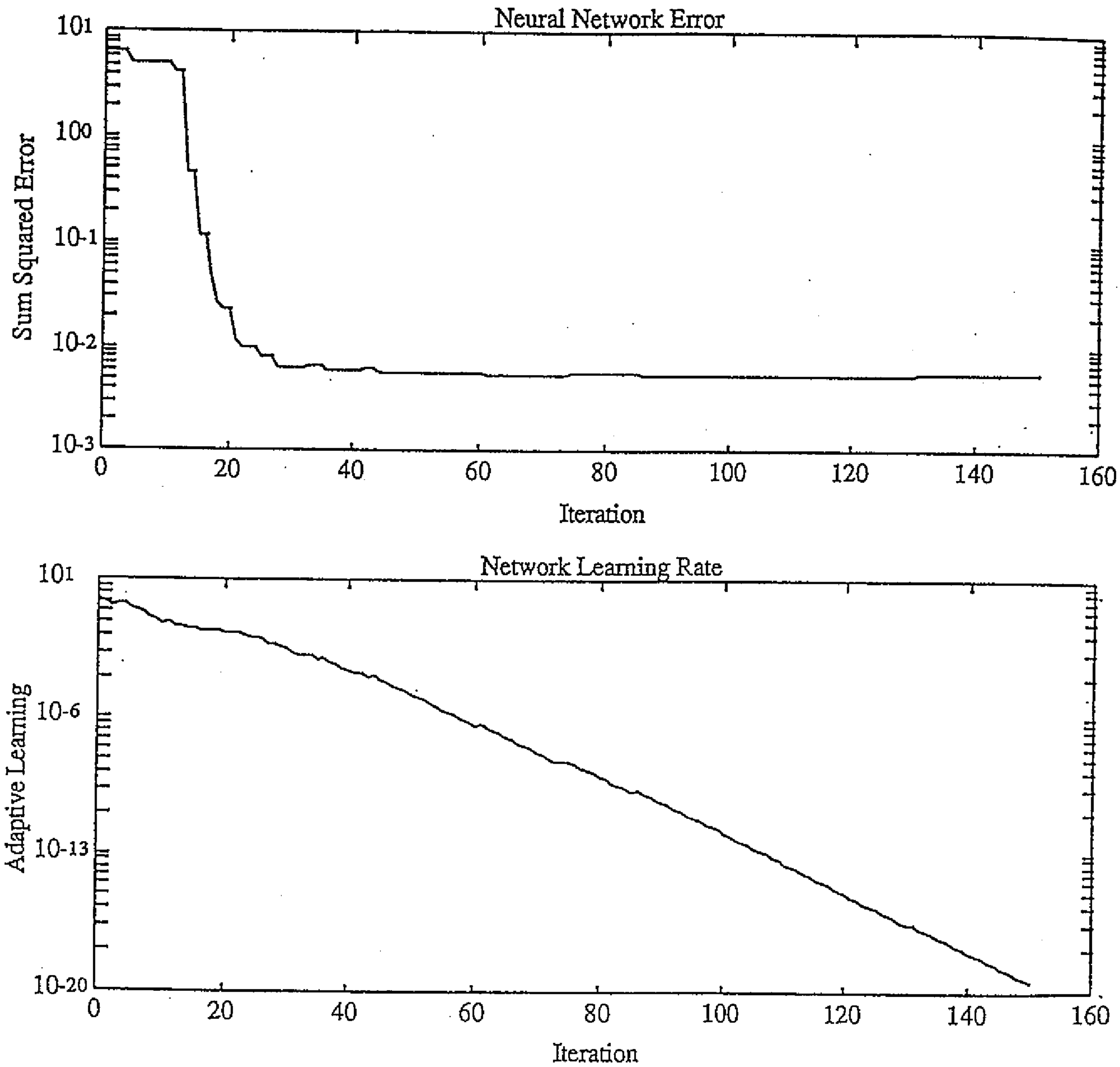

Figure 4. SSE and adaptive learning of a typical neural network identification process.

5. CONTROL PROCESS USING NEURAL NETWORK

The ANN technique used for the identification process is also used for the control process. The identification ANN and the control ANN have the same architectural structure, i.e. the same number layers and the same number of nodes for each layer, and use the same mathematical operators, i.e. the same transfer functions and the same learning back-propagation algorithm.

However, the two ANNs act, as part of the indirect MRAC system, in two distinct and different fashions. While, the identification ANN is in charge of upgrading the value of the connecting weights and of the biases of each node of the ANN, the control ANN is responsible for the control of the plant.

The control ANN calculates the output of the plant and the difference between the output of the plant and the prescribed output of the reference model. The resulting value is then utilized to determine the control action. This is achieved minimizing the following cost function, J,

$$J = [y_{NN}(t) - y_m(t)]^2 \quad , \tag{21}$$

with,

y_{NN} = output variable calculated by the control ANN,
y_m = output variable calculated by the reference model.

In this study, the output variable of the control ANN is the outlet steam temperature, T_{wo}, and the output of the reference model is the desired set point of the outlet steam temperature of the plant, T_{set}. Therefore the resulting cost function is,

$$J_{sv} = [T_{wo}(t) - T_{set}(t)]^2 \quad . \tag{22}$$

The control action is obtained acting on the feedwater flow rate variable.

6. MODEL REFERENCE ADAPTIVE CONTROL SYSTEM USING NEURAL NETWORK

The overall control action performed by the indirect MRAC system combines the action of the identification ANN and the action of the control ANN.

The control action of the indirect MRAC system begins with the implementation of the control ANN. The cost function, J_{ev}, generated by the control ANN, is minimized using the Simplex method[8], which is a widely used method for minimization or maximization of functions. The Simplex method calculates the value of the control variable, which minimizes the cost function, J_{ev}. This value is used as input for the plant and for the identification ANN.

The subsequent output of the plant, y_p, is used for two purposes:
(a) as input to the identification ANN which, initiates an iterative training procedure to find the new connecting weights and biases of the ANN nodes that minimize the SSE, (this process is performed on line), and which introduces the new set of values in the control ANN and the identification ANN;
(b) as input for the control ANN, whose connecting weights and biases have already been upgraded by the identification ANN, in order to determine the action for the subsequent time step.

The action of transferring the values of the connecting weights and of the biases of the nodes of the identification ANN to the control ANN is achieved in the computer algorithm of the indirect MRAC system storing them in the same address of the memory area.

The flow chart representing the control action of the indirect MRAC system using the ANN technique is shown in Figure 5.

7. DISCUSSION AND RESULTS

The efficacy of the indirect MRAC system has been tested for transients related to variations of some of the input variables and for transients related to variations of some of the internal parameters of the plant.

In the first case two transients have been performed starting from steady state conditions at 100% power. One transient results in a 10% ramp increase in the inlet sodium temperature. The other transient results in a 20% ramp decrease in the sodium flow rate together with a 10% ramp decrease in the sodium inlet temperature. The results of the above transients are shown in Figure 6 and Figure 7 respectively.

In the second case one transient has been performed. Starting from steady state and 100% power a ramp decrease varying between 10% to 20%, has been introduced in each one of the heat transfer coefficients. The results of this transient are presented in Figure 8.

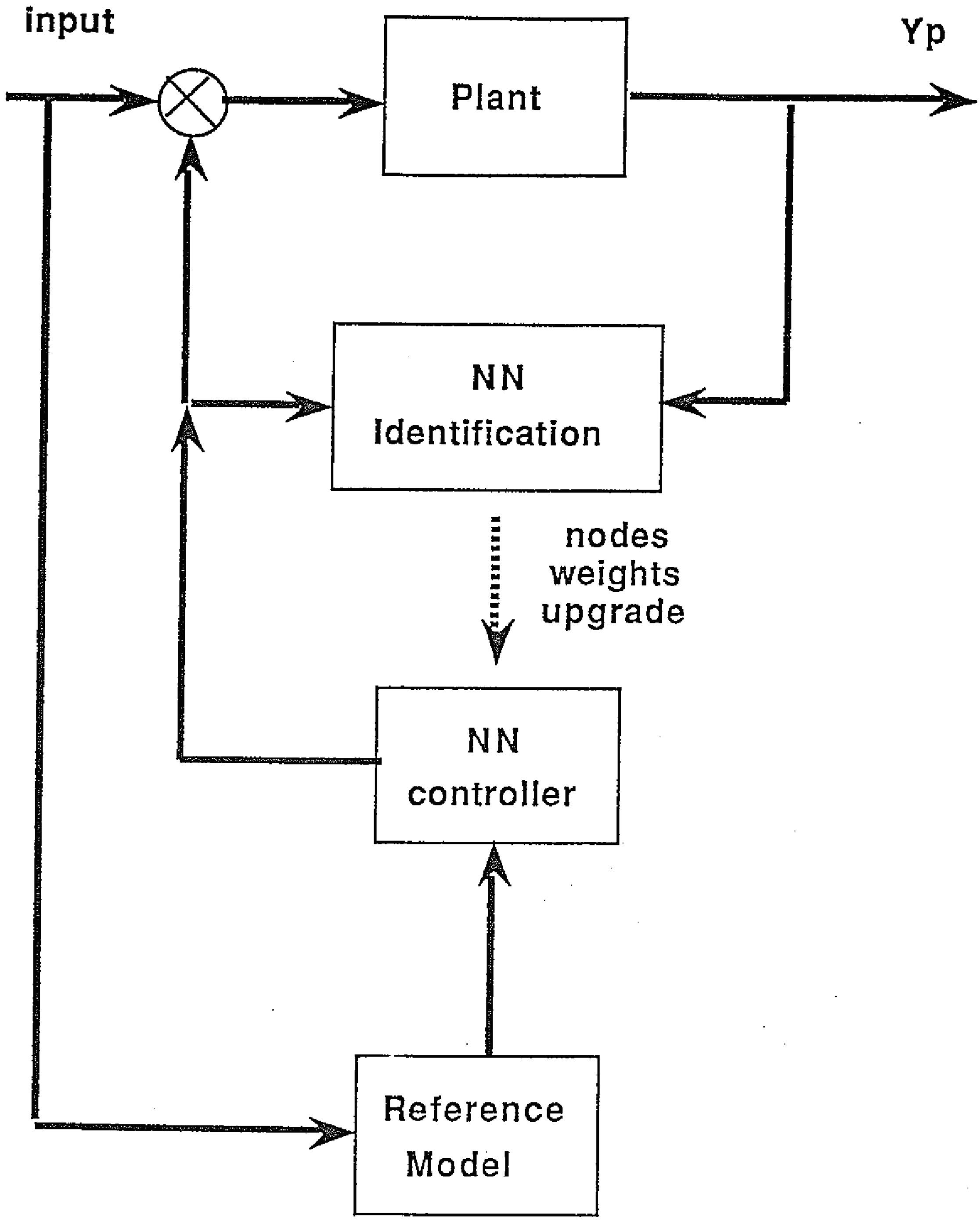

Figure 5. Indirect model reference adaptive control system using neural network.

Both cases show that the indirect MRAC system is very effective in keeping the outlet steam temperature close to its set point.

The same cases have been studied using a typical proportional integral (PI) control system,

$$W_{fw}(t+1) = W_{fw}(t) + P(t) + I(t) \quad , \tag{23}$$

where P(t) is the proportional term,

$$P(t) = k_1\left(\frac{T_{wo}(t)}{T_{set}(t)} - 1\right) \quad , \tag{24}$$

I(t) is the integral term,

$$I(t) = \frac{P(t)}{tt_1} + \frac{I(t-1)}{tt_2} \quad , \tag{25}$$

and tt_1, tt_2, and k_1, are the adjustable parameters of the PI control system. In this study tt_1, tt_2, and k_1, have been determined using a trial-and-error procedure.

The results, shown in Figure 9 and Figure 10, show that the PI control system is less efficient than the indirect MRAC system in both cases.

The adaptation capability of the ANN has been tested with two transients. One transient results in a 10% ramp decrease in the sodium inlet temperature together with a 20% ramp decrease in the sodium flow rate. The other transient results in an 10% ramp increase and a subsequent 10% ramp decrease of the sodium inlet temperature leaving the plant at steady state conditions.
Figure 11 shows the variation of the connecting weights of each node of the hidden layer during the first transient. It is shown that the connecting weights are adjusting to a new steady situation determined by the action of the controller. Figure 12 shows the variation of the connecting weights of each node of the hidden layer for the second transient. As expected the connecting weights of the nodes adapt to the transient and they return to their previous values once the plant is brought back to the original steady state conditions.

The importance of the on line adaptation mechanism has also been tested changing the number of on line iterations performed by the identification ANN during a transient. Since the computation time of the transient highly depends on the number of the on line iterations performed by the identification ANN, it is important to try to minimize it, without affecting the efficiency of the indirect MRAC system. The test shows that, if the number of iteration is not large enough, the indirect MRAC system fails. For the transient considered in this example, the indirect MRAC system fails to control the plant if less than twelve iterations are used for the on line identification. The efficiency of the indirect MRAC system depends on the number of on line iterations used. As shown in Figure 13, the optimal number of on line identification iteration is around twenty. For larger number of iterations there is not an appreciable improvement in the efficacy of the indirect MRAC system.

8. CONCLUSIONS

In this paper, a model reference adaptive control system using ANN has been applied to control the outlet steam temperature of a sodium to water once-through helical coil type evaporator.

A nonlinear dynamic model has been developed to simulate the evaporator.

The efficacy of the model reference adaptive control system has been tested with several transients. The response of the model reference adaptive control system, when a transient is introduced in the plant, is better than the response of a typical proportional integral control system.

The capability of the ANN to modify its parameters, connecting weights and biases, has been presented. The ANN intrinsic characteristics perfectly suits the adjustment property required by the adaptive control strategy.

Also it has been shown that the performance of the model reference adaptive control system strongly depends on the on line adjustment of the parameters of the identification ANN.

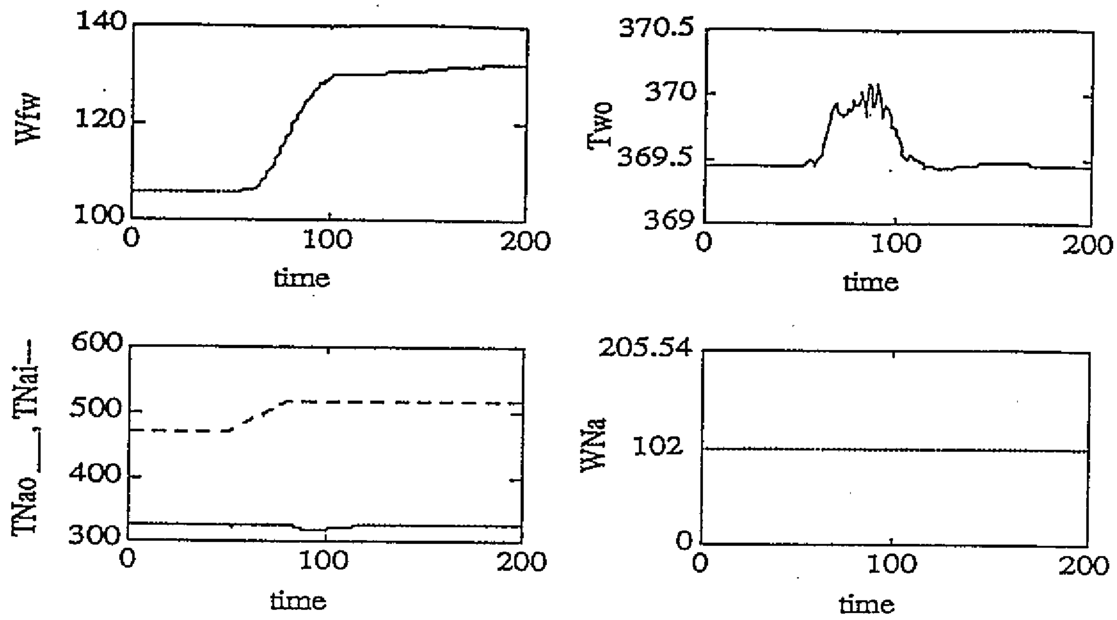

Figure 6. Outlet steam temperature, T_{wo}, feedwater flow rate, W_{fw}, sodium flow rate W_{Na}, and outlet sodium temperature, T_{Nao}, during a 10% increase in inlet sodium temperature, T_{Nai}, transient.

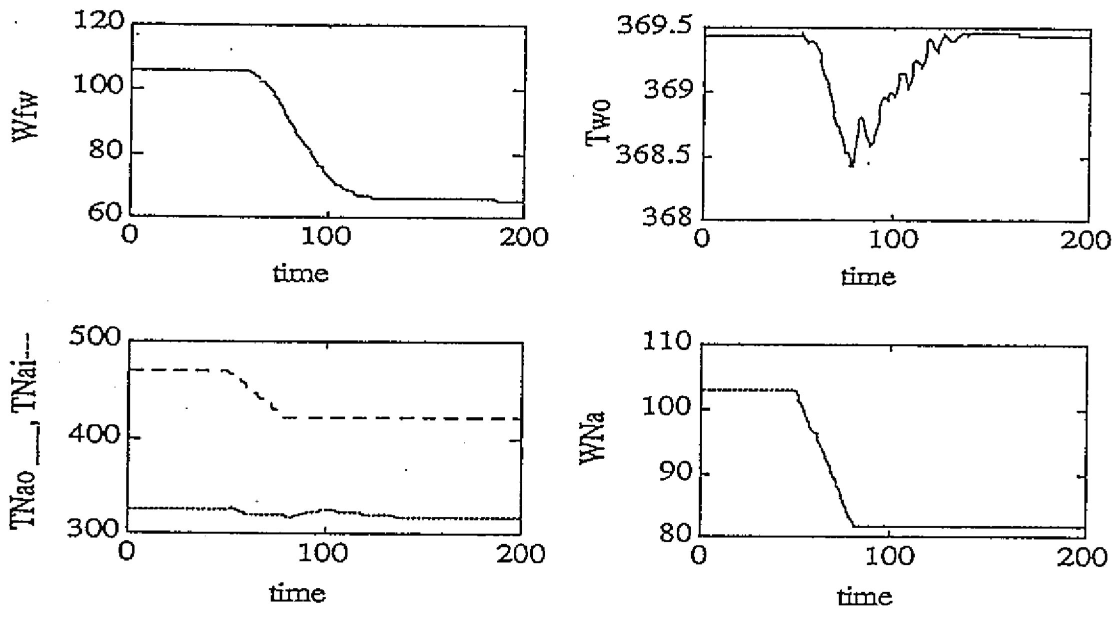

Figure 7. Outlet steam temperature, T_{wo}, feedwater flow rate, W_{fw}, and outlet sodium temperature, T_{Nao}, during a 10% decrease in inlet sodium temperature, T_{Nai}, and a 20% decrease in sodium flow rate, W_{Na}, transient.

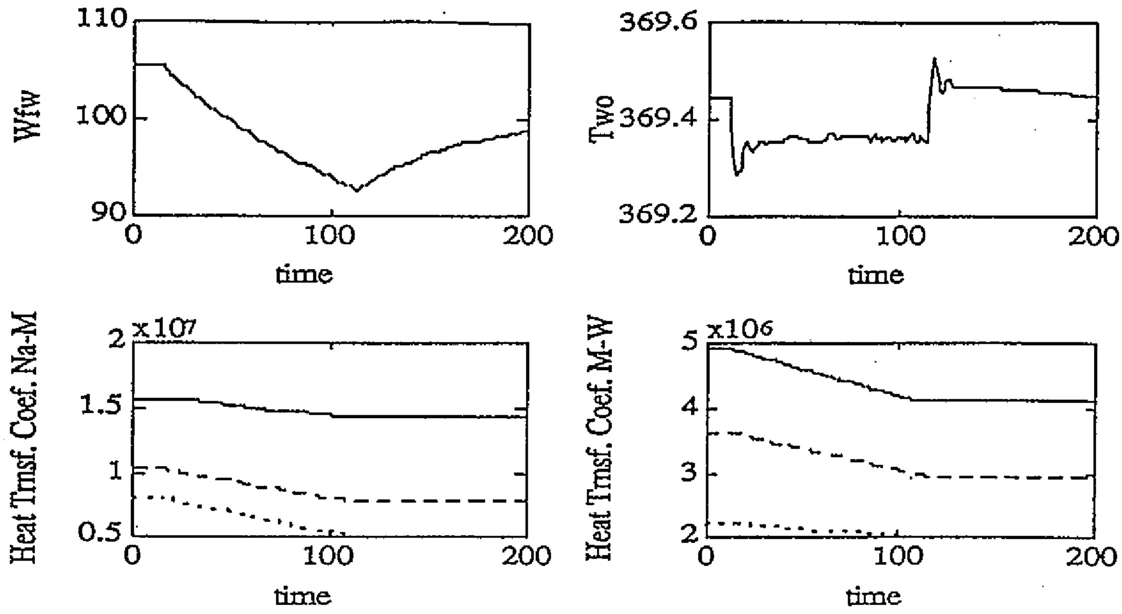

Figure 8. Outlet steam temperature, T_{wo}, and feedwater flow rate, W_{fw}, during a variation of the sodium to metal and metal to fluid heat transfer coefficients transient.

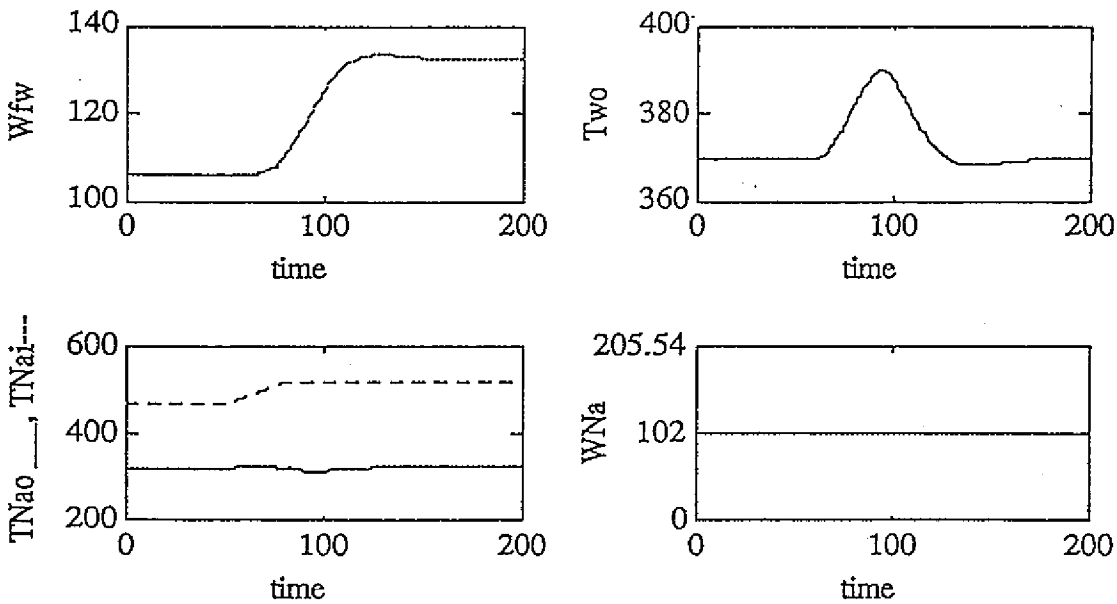

Figure 9. Outlet steam temperature, T_{wo}, feedwater flow rate, W_{fw}, sodium flow rate W_{Na}, and outlet sodium temperature, T_{Nao}, during a 10% increase in inlet sodium temperature, T_{Nai}, transient, using a proportional integral control system.

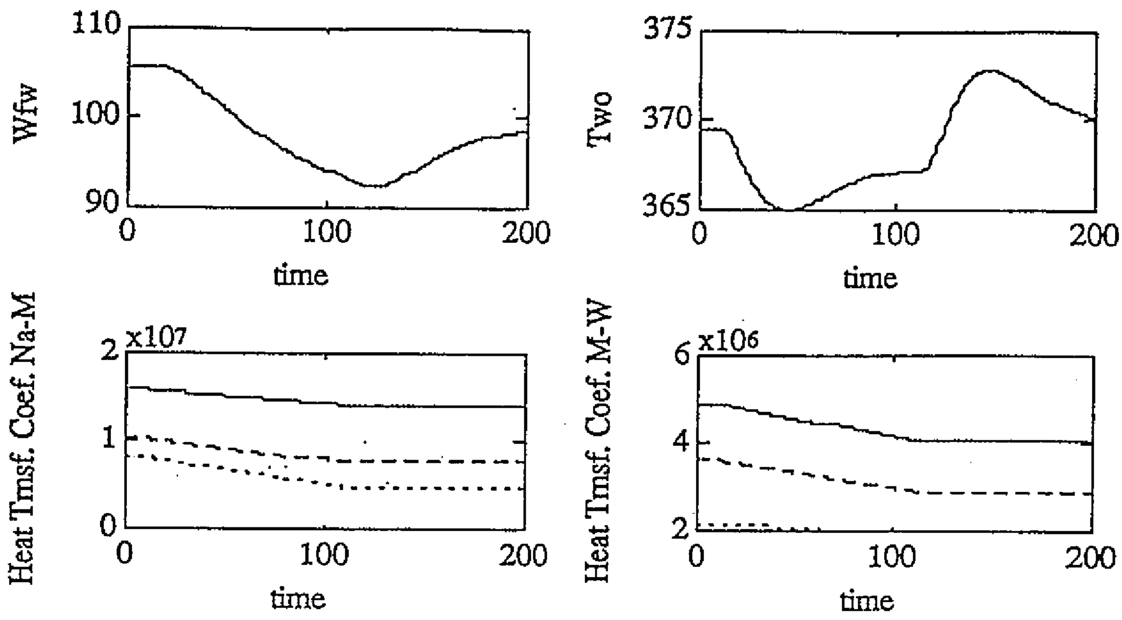

Figure 10. Outlet steam temperature, T_{wo}, and feedwater flow rate, W_{fw}, during a variation of the sodium to metal and metal to fluid heat transfer coefficients transient, using a proportional integral control system.

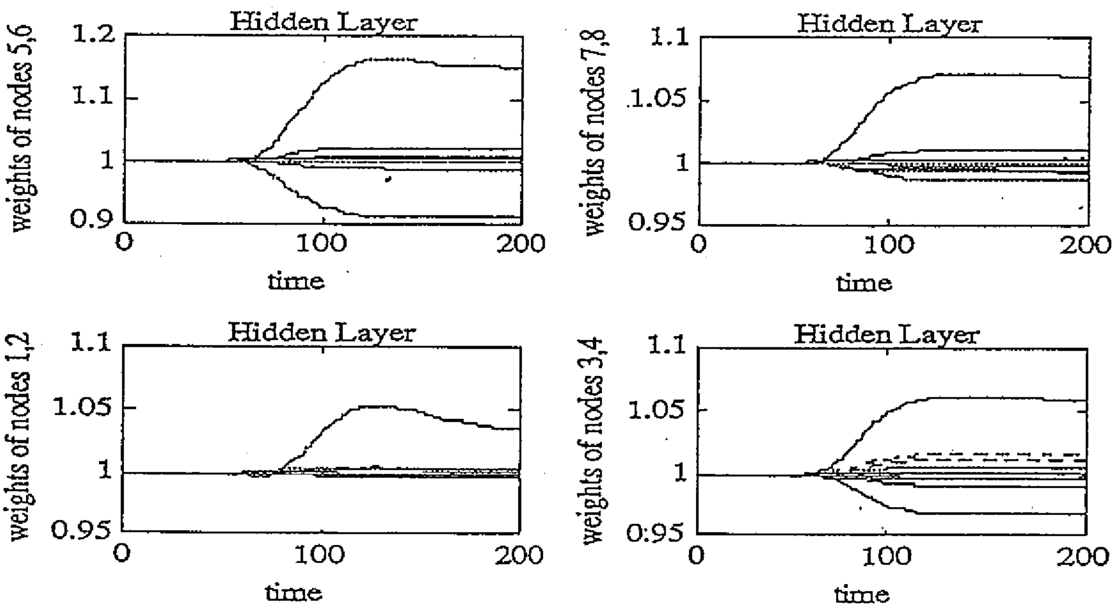

Figure 11. Hidden layer nodes normalized connecting weights adjustment during a 10% decrease in inlet sodium temperature, T_{Nai}, and a 20% decrease in sodium flow rate, W_{Na}, transient.

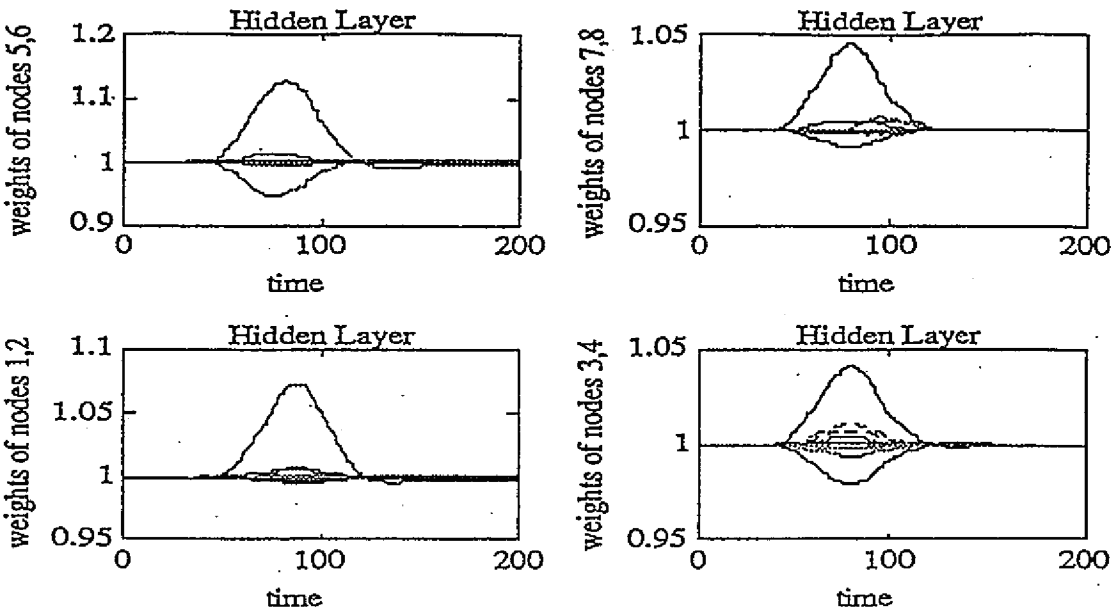

Figure 12. Hidden layer nodes normalized connecting weights adjustment during a 10% increase and a 10% decrease in inlet sodium temperature, T_{Nai}, transient.

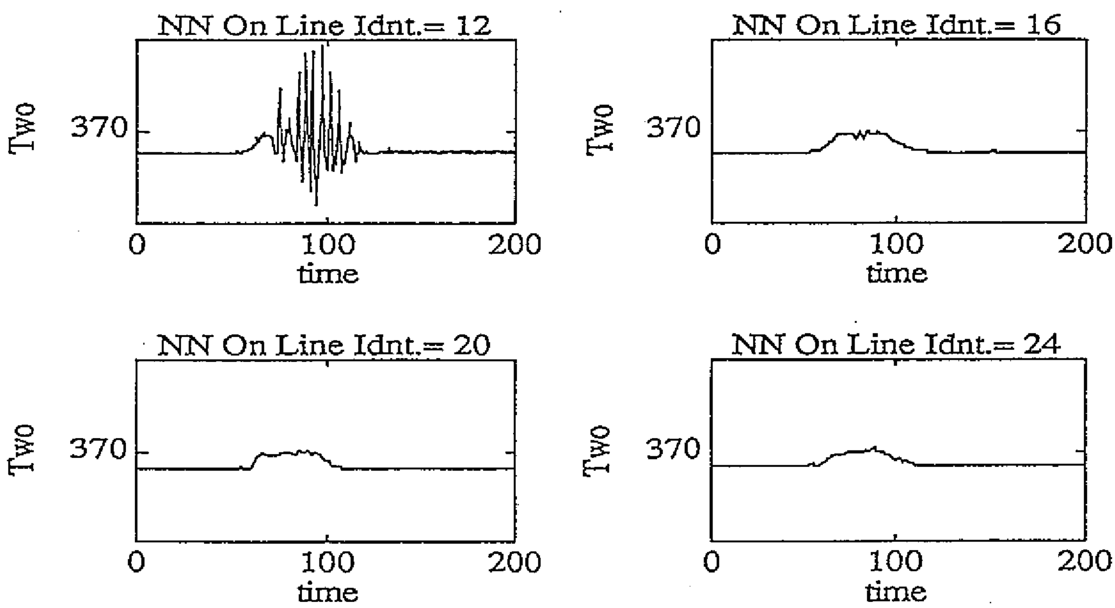

Figure 13. Outlet steam temperature, T_{wo}, during a 10% increase in inlet sodium temperature, T_{Nai}, transient, using 12, 16, 20, and 24 on line identification iterations.

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