PNC TN9410 95-210

Neural Network Predictive and Anticipatory Control Algorithms for a Neural Adaptive Control System

September 1995

O-arai Engineering Center
Power Reactor & Nuclear Fuel Development Corporation

PNC TN9410 95-210
September, 1995

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ABSTRACT

The proper control of the outlet steam temperature of the evaporator is of major importance for improving the overall performance of the balance of plant of a nuclear power reactor. This report presents a predictive and an anticipatory control algorithms based on the artificial neural network (ANN) technique. The two control algorithms are embedded on a model reference adaptive control system based on the ANN technique, defined as $MRAC_{nn}$. It has already been illustrated that nonlinear dynamical systems such as the evaporator of a nuclear power plant can be controlled by an $MRAC_{nn}$ system. However, little attention has been devoted on exploiting the forecasting potential of the ANN technique for enhancing the accuracy and improving the efficacy of the control action of the $MRAC_{nn}$ system. The improved $MRAC_{nn}$ system has been tested to simulate the behavior of a fast breeder reactor (FBR) evaporator and to control its outlet steam temperature. The simulation results indicate that the performance of the $MRAC_{nn}$ system substantially improves when the predictive and the anticipatory control algorithms are activated.

*PNC International Fellowship Awardee

PNC TN9410 95-210
1995年9月

対象挙動と境界条件のニューラルネットワークによる予測アルゴリズムの適応制御への適用

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要旨

蒸気発生器の出口蒸気温度の正確な制御は、原子力発電所の水／蒸気系全体の性能を向上させるために重要である。本報告書では、制御対象の挙動予測及び制御対象の上流で時間的に先行して観測される境界条件をニューラルネットワークによって制御信号に反映させるアルゴリズムについて述べる。このアルゴリズムはニューラルネットワークを用いたモデル適応制御手法(MRACnn)に組み込まれている。MRACnnが原子炉の蒸気発生器のような非線形な機器をも制御できることは既に報じられているが、MRACnnシステムの性能向上のためにニューラルネットワークの特性を更に利用する手法については今まで考えられていなかった。本報告書に述べるMRACnnの改良型は高速炉プラントシミュレータと接続して、蒸気発生器出口蒸気温度の制御に用いられた。この結果、制御対象の挙動予測及び制御対象の上流で時間的に先行して観測される境界条件を制御信号に反映させることが制御性能を向上させることを確認した。

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CONTENTS

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1. INTRODUCTION

The conscious generation of predictive models for the purpose of control is one of the basic characteristics of human intelligence[1]. Man performs no action without forecasting in sufficiently precise form the consequences and the effects of the action.

The ANN technique, a mathematical method tending to represent the behavior of the brain cells, seems the best instrument to simulate this inherent quality of the human thinking.

Generalized predictive control systems[2] and anticipatory control systems[3,4] are two means of implementing a forecasting behavior in the control action of linear and nonlinear dynamical systems. However the application of such control systems highly depends on the input/output data transfer relationship of the system being controlled whose mathematical model representation in the case of complex nonlinear systems is quite often difficult if not impossible to attain with traditional mathematical tools.

Although the implementation of the ANN technique for the identification and control of dynamical nonlinear systems has already been suggested[5], its forecasting and learning capability has not yet been exploited for the purpose of enhancing the performance of these control systems.

This report focuses on the development of a predictive and an anticipatory control algorithms based on the ANN technique. The two control algorithms have been embedded in the control process of an $MRAC_{nn}$ system[6], a model reference adaptive control system with ANN identification and ANN control mechanisms. Simulation and performance tests of the improved $MRAC_{nn}$ have been performed on a nonlinear dynamical mathematical model of an FBR evaporator.

The remainder of the report is organized as follow. Section 2 presents a succinct description of the types of multilayer ANN which are used throughout this report. The ANN based predictive and anticipatory control algorithms are illustrated in section 3. Their implementation on an $MRAC_{nn}$ system is described in section 4. In section 5 the simulation results and the performance of the $MRAC_{nn}$ improved by the two ANN control algorithms in controlling the outlet steam temperature of an FBR evaporator are presented and discussed. Finally, some conclusive remarks are proposed in section 6.

2. MULTILAYER ARTIFICIAL NEURAL NETWORK

The principal characteristics of multilayer ANN[7] a fast-emerging branch of the science of artificial intelligence, are briefly summarized in this section. ANNs are nonlinear data processing systems with efficient input-output mapping capability, composed of many nonlinear computational elements called nodes that can be grouped and connected in several modes.

In a multilayer ANN the nodes are grouped in layers. Each node of a layer is fully connected with those of the adjacent layers, while no connection exists within each layer. These connections are defined as connecting weights. The connecting weights are adjustable and adaptive parameters that represent the input/output relationship of the system. The structural architecture of a multilayer ANN can be configured in a feedforward and in a recurrent scheme. In a feedforward multilayer ANN the nodes of the input and the output layer are not connected. On the other hand a recurrent multilayer ANN has its output nodes connected with the related input ones. The multilayer ANN used in this report consists of one input, one hidden and one output layer.

The input/output mapping can be achieved with a variety of linear and nonlinear transfer functions. Here, the hypertangent sigmoidal activation function[8], which maps the inputs to the nodes from the interval $(-\infty,+\infty)$ to the interval $(-1,1)$ is used in the input and in the hidden layer and a linear activation function is used in the output layer[8]. The tuning of the connecting weights, that is of fundamental importance for a successful performance of the ANN technique, is obtained with the classical back-propagation method[9], improved with momentum[10] and adaptive learning[10], to overcome local minima problems and to reduce the training time respectively. The algorithm is shown in the following expression,

$$w^m(t+1) = w^m(t) + \eta\,\delta^m X^{m-1} + \mu\left[w^m(t) - w^m(t-1)\right], \qquad (1)$$

where,

w^m = connecting weight of layer m,
η = gain factor of the learning rate,
μ = gain factor of the momentum,
δ^m = generalized delta value (i.e. error of the node of the mth layer),

X^m = output of a node of the mth layer, and
t = presentation number of the learning iteration.

The complete definition of the ANN structure (i.e. the number of nodes for each layer) highly depends on the characteristic of the problem at hand. There is not yet an established mathematical method to determine the number of nodes for each layer. However, since the calculation time increases with the number of nodes it seems wise to keep their number as low as possible, particularly when dealing with the on-line monitoring and control of real-time environments.

3. ANN PREDICTIVE AND ANTICIPATORY CONTROL ALGORITHMS

This section describes the development of the predictive and the anticipatory control algorithms using the ANN technique.

3.1 ANN Predictive Control Algorithm

Predictive controllers are designed to calculate future control signals which minimize a multistage cost function defined over a specific time interval. Their applications is limited to system whose future desired outputs are known (i.e. when a fixed set point or a trajectory must be attained during operation).

An ANN predictive control algorithm is defined by a cost function J_p,

$$J_p = \sum_{i=1}^{N_p} \left[Ynn_k(t+i) - Yrm(t+i) \right]^2 , \tag{2}$$

where,

N_p = range of prediction,
Ynn_k = ANN output of the variable to be controlled, and
Yrm = reference model output.

The range of prediction N_p settles the distance between the actual time and the future time output of the system. The reference model output Yrm

represents the prescribed future outputs of the system.

The control action is performed using the ANN with recurrent configuration. The recurrent iterative procedure is based on the range of prediction N_p and it is performed at each time step of the control action. The optimization of N_p is determined with a trial-and-error procedure.

3.2 ANN Anticipatory Control Algorithm

An anticipatory system is one whose present behavior depends in some fashion upon future inputs. Suppose we have a system ***A*** and another system ***B*** whose time parameters can be chosen arbitrarily with respect to the real-time of ***A*** such that the present state of one or more of the variables ***b(t)*** representing ***B*** describes the state of one or more variables ***a(t+h)*** representing ***A*** at same later instant of real-time ***h***. In this case ***h*** represents the anticipation time interval separating system ***A*** from ***B***. If we allow the output of ***B*** to be an input of ***A***, we originate a situation in which a future state ***a(t+h)*** of ***A*** controls the present transition in ***A***[4].

An ANN anticipatory control algorithm is defined by a cost function J_a,

$$J_a = \sum_{i=1}^{N_a} \left[Ynn_k(t+i) - Yrm(t+i) \right]^2 , \tag{3}$$

where,

N_a = anticipation time,
Ynn_k = ANN output of the variable to be controlled, and
Yrm = reference model output.

with the condition that at each time step,

$$Y_a(t) = B_a(t - N_a) , \tag{4}$$

where,

Y_a = input variable of ***A*** related to the anticipatory system ***B***,
B_a = output variable of ***B*** related to the controlled system ***A***.

The pertinent variables of the anticipatory system ***B*** (i.e. those coupled with the system ***A***) are introduced as input to the ANN.

The ANN anticipatory control algorithm is applied using the ANN with recurrent configuration in the same fashion used for the predictive control. The recursive iteration is based on the anticipatory time N_a, whose optimal value cannot exceed the time interval dividing the two systems. The ANN anticipatory control can and will be performed only if a variation occurs in the anticipatory system.

4. IMPLEMENTATION ON AN MRAC$_{nn}$ SYSTEM

The development of an MRAC$_{nn}$ has already been discussed by the author in the report PNC ZN9410 94-069.

The ANN predictive and the anticipatory control algorithms are combined together and inserted in the ANN control process of the MRAC$_{nn}$ through the cost function J_{ap},

$$J_{ap} = J_p + J_a + J_u, \tag{5}$$

where J_p, and J_a are the cost functions of the predictive and of the anticipatory control algorithm, and J_u,

$$J_u = \sum_{i=1}^{N_u} \left[W_u \left(\Delta U (t+i)^2 \right) \right], \tag{6}$$

with

N_u = control horizon, determining the number of future control actions to be calculated,
W_u= control weight of the control horizon,
Δ = differencing operator, and
U = control variable,

and with the condition that

$$\Delta U(t+i) = 0, \quad \text{if} \quad i > N_u \ , \tag{7}$$

is a cost function that acts as a smoothing mechanism for the control action and has the role to avoid large variations of the control variable U between two or more consecutive time steps. The control input U is calculated with the "downhill simplex method" due to Nelder and Mead (1965).

The two control algorithms are performed sequentially at each time step of the simulation. The ANN control process checks if a variation occurs in one of the anticipatory variables B_a and initiates the ANN anticipatory control algorithm. Once the calculation of the anticipatory control algorithm has been completed, the ANN predictive control algorithm is started. If there is no variation in B_a the ANN control process sets N_a equal to zero and directly activates the predictive control algorithm.

5. SIMULATION RESULTS AND DISCUSSION

The performance tests have been performed on a nonlinear mathematical model of an FBR evaporator using the MATLAB High-Performance Numeric Computation Software on a Unix work-station. The boundaries of the model are the inlet and outlet nozzles of the liquid sodium and the inlet nozzle of the feedwater and the outlet nozzle of the steam. A detailed mathematical description of the FBR evaporator model can be found in Reference 6.

The intermediate heat exchanger (IHX) has been regarded as the anticipatory system linked to the FBR evaporator. Its outlet sodium temperature is the anticipatory variable and it is coupled to the inlet sodium temperature of the FBR evaporator with anticipation time N_a inversely proportional to the flow rate of the secondary sodium and directly proportional to the physical distance separating the two components. It is assumed that a variation of the sodium temperature in the outlet nozzle of the IHX will appear after a time interval N_a in the sodium inlet nozzle of the FBR evaporator.

The structure of the multilayer ANN simulating the FBR evaporator mathematical model consists of three layers with respectively seven input, ten hidden, and four output nodes. The input variables are the feedwater flow rate, the outlet temperature, enthalpy, and pressure of the steam, the outlet and inlet sodium temperature, and the outlet sodium temperature of the IHX. The output variables are the outlet temperature, enthalpy, and pressure of the steam, and the outlet sodium temperature.

The application of the $MRAC_{nn}$ to the FBR evaporator is straightforward. An initial training of the ANN is performed off-line with the FBR at nominal full reactor (100%) power by introducing random perturbations to the inlet sodium temperature and to the feedwater flow rate. The training of the ANN is kept active at each time step during normal operation. The output of the reference model Yrm is the prescribed set point of the outlet steam temperature. The controlled variable Ynn_k is the outlet steam temperature whose value should follow a constant set point allowing an optimal utilization of the connected FBR superheater. The control variable U is the feedwater flow rate.

The FBR evaporator has been tested starting at steady state conditions at 100% power inducing several ramp transients in the inlet sodium temperature and in the sodium flow rate. However, in this report, the tests presented are limited to variations of the anticipation time N_a and of the range of prediction N_p, based on a 10% ramp increase in the inlet sodium temperature at 8% per minute rate. The ramp transient of the inlet sodium temperature is kept unchanged during all the subsequent tests and used as benchmark to verify the efficiency and the efficacy of the predictive and the anticipatory control algorithms within the $MRAC_{nn}$ system. The control horizon N_u, and its weighting factor W_u have been set to 1 and .8 respectively. The figures show the normalized values of the variables.

Figure 1 (top of the next page) shows the trend of the inlet sodium temperature (upper part) and the trend of the related outlet steam temperature (lower part) when the predictive and the anticipatory control algorithm are not applied to the $MRAC_{nn}$ system.

Figure 2 (bottom of the next page) shows the trend of the outlet steam temperature with anticipatory control and without predictive control in the $MRAC_{nn}$ system. The anticipation time N_a is set to 2.5, 5, and 10 seconds.

It is possible to notice how the action of the anticipatory control smooths down the outlet steam temperature at the beginning of the transient. The $MRAC_{nn}$ acts based on the information from the IHX provided through the anticipatory control algorithm. The rise of the outlet steam temperature is prevented by increasing, ahead in time, the feedwater flow rate. The performance of the $MRAC_{nn}$ increases with the anticipation time interval N_a. However, a large anticipation could be counterproductive. Therefore the size of N_a should be optimized using a trial-and-error procedure.

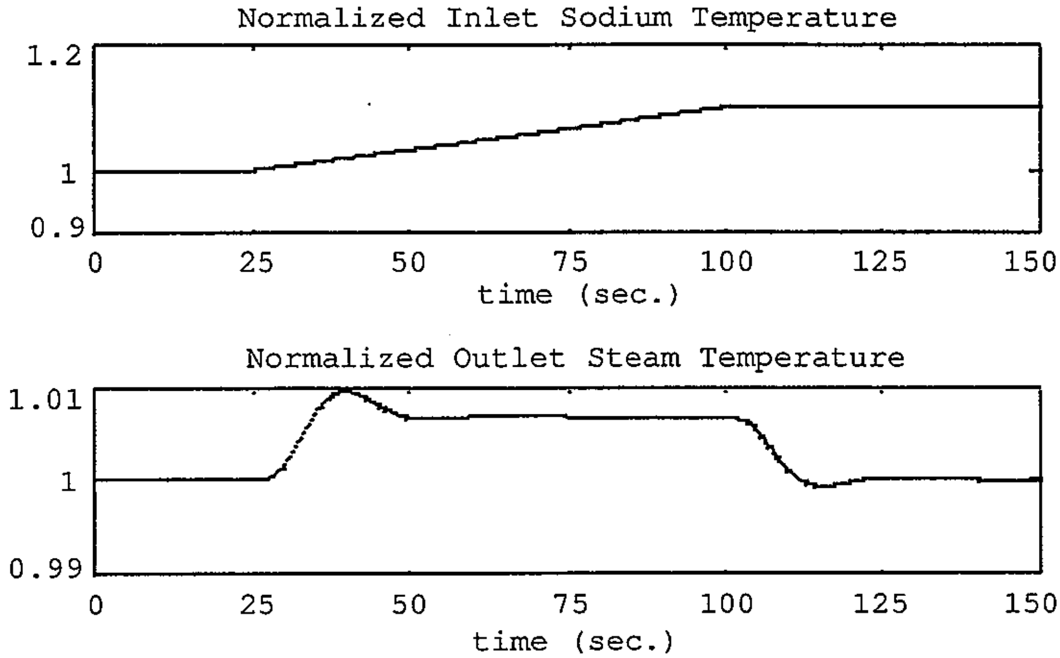

Figure 1. Normalized outlet steam temperature for a 10% increase in inlet sodium temperature with no anticipatory and predictive control.

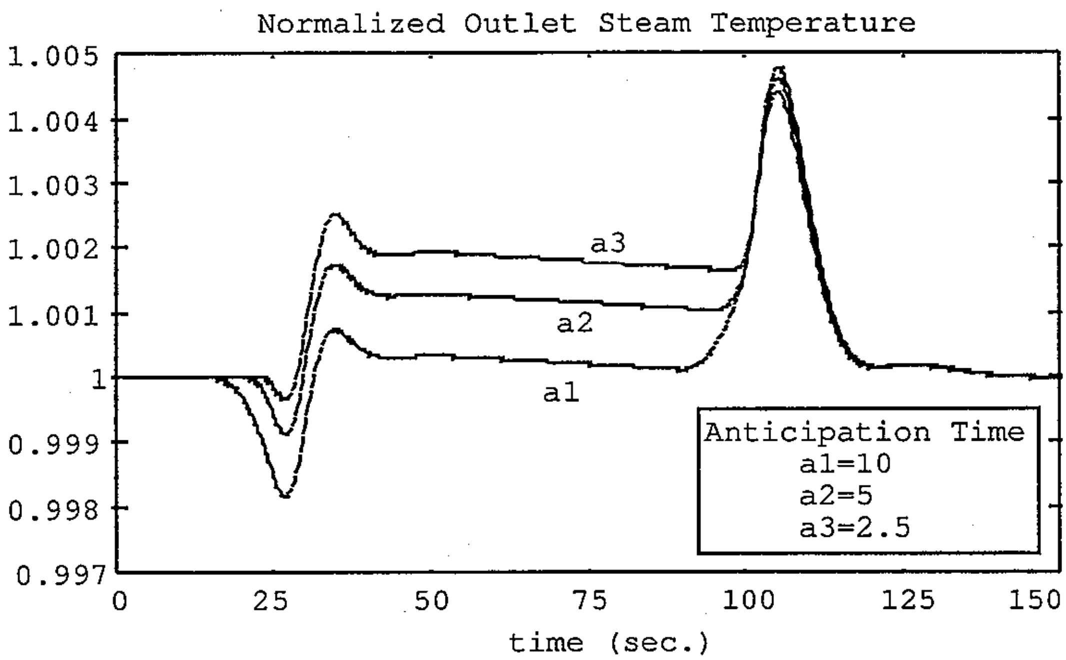

Figure 2. Normalized outlet steam temperature for a 10% increase in inlet sodium temperature with no predictive control and with anticipation control time of 2.5, 5, and 10 sec.

The anticipatory control has, as expected, a minimal effect toward the end of the transient were no anticipating information is provided to the $MRAC_{nn}$.

Figure 3 shows the trend of the outlet steam temperature with predictive control and without anticipatory control. The range of prediction N_p is set to 1.25, 2.5, 5, and 10 seconds.

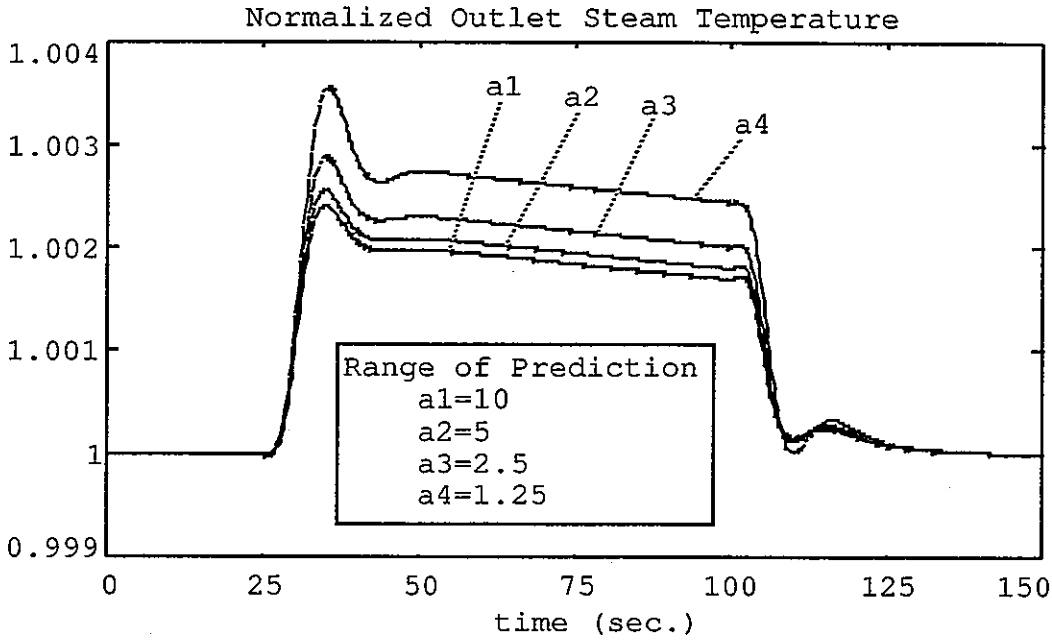

Figure 3. Normalized outlet steam temperature for a 10% increase in inlet sodium temperature with no anticipatory control and with range of prediction of 1.25, 2.5, 5, and 10 sec.

The action of the predictive control smooths down the outlet steam temperature through all the transient but it is particularly effective toward the end of the transient. Also in this case the performance of the $MRAC_{nn}$ increases with the range of prediction N_p. However, there is an upper bound saturation threshold for the value of N_p. Thus, when the N_p is larger than 10 seconds, the action of the $MRAC_{nn}$ does not show any appreciable improvement.

Figure 4 (next page) shows the trend of the outlet steam temperature when the predictive and the anticipatory control are applied together. The anticipation time N_a is set at 2.5 seconds and the range of prediction N_p is set to 0, 1.25, 2.5, and 10 seconds.

As expected the best results are obtained with the combined action of the anticipatory and the predictive control. The anticipation interval N_a has been chosen equal to 2.5 seconds because larger values did not show appreciable improvement when combined with a predictive action. It is worth noting that the action of the predictive control progressively smooths, with the increasing of the range of prediction N_p, the peak located near time 100 seconds in the transient. Subsequent increments of N_p did not bring any considerable improvement to the control action of the $MRAC_{nn}$ system.

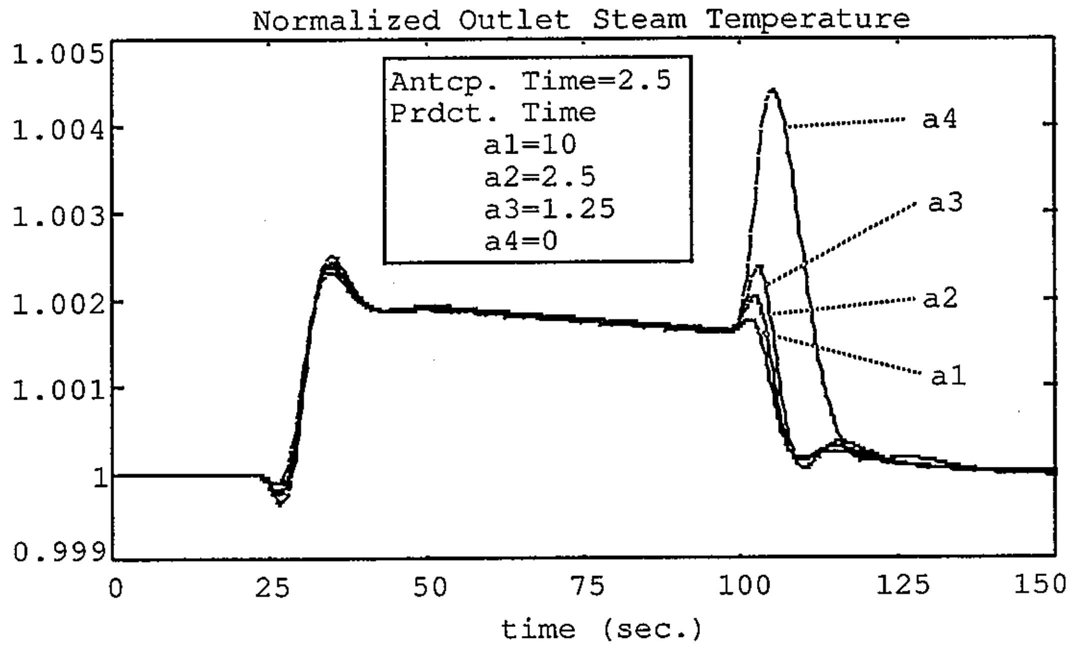

Figure 4. Normalized outlet steam temperature for a 10% increase in inlet sodium temperature with anticipation control time of 2.5 sec. and range of prediction of 0, 1.25, 2.5, and 10 sec.

The improvement introduced in the performance of the $MRAC_{nn}$ system by the anticipatory and control algorithms is evident and it can be quantified by comparing the results of Figure 1, where no predictive and anticipatory control action are performed, with the ones of the remaining figures.

6 . CONCLUSIONS

The development of a predictive and an anticipatory control algorithm using the ANN technique to enhance the performance of the control action of an $MRAC_{nn}$ system has been presented in this report. The control action of the improved $MRAC_{nn}$ has been validated to control the outlet steam temperature of a stand alone model of an FBR evaporator. The results show that the performance of the control action improves when the ANN predictive and anticipatory control algorithms are both implemented and activated in the ANN control process of the $MRAC_{nn}$ system.

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