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Predictive Control Based on an Auto-Regressive Neuro-Fuzzy Model Applied to the Steam Generator Startup Process at a Fossil Power Plant

Control Predictivo Basado en un Modelo Neurodifuso Auto-Regresivo Aplicado al Proceso de Arranque del Degenerador de Vapor de una Unidad Termoeléctrica

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Abstract

This paper presents an application of artificial intelligence techniques for the improvement of the operation of a thermoelectric unit. The capacity for empirical learning gained from artificial intelligence systems was utilized in the development of the strategy. A neuro-fuzzy model for the steam generator startup process is obtained from experimental data. Ultimately, the neuro-fuzzy model is combined with a predictive control algorithm to produce a control strategy for the heating stage of the steam generator. This provides the operators at the fossil power plant with the necessary information to efficiently accomplish the heating process. The information gained from the control strategy is not directly applied to an automatic control scheme; instead it is presented to the operator who then decides on its application. Therefore, in this way the information is used to develop a strategy that takes into consideration the personal capacity and the working routine of the operator. The simulation tests that were carried out demonstrated the feasibility and the beneficial results that can be obtained from the application of any of the three variants of predictive control proposed in this paper.

Keywords: Predictive control, optimization, ANFIS, auto-regressive model, steam generator, fossil power plant.

Resumen

En este trabajo se presenta una aplicación de técnicas de inteligencia artificial al mejoramiento de la operación de una unidad termoeléctrica. El desarrollo llevado a cabo aprovecha la capacidad de aprendizaje a partir de experiencias, que ofrecen los sistemas basados en inteligencia artificial. Usando datos experimentales, se obtiene un modelo neuro-difuso del comportamiento del arranque de un generador de vapor. Posteriormente, este modelo se combina con un algoritmo de control predictivo para construir una estrategia de control para la etapa de calentamiento del generador de vapor, la cual permite ofrecer a los operadores de la unidad termoeléctrica la información requerida para llevar a cabo de manera eficiente el calentamiento. La información generada por la estrategia de control no se aplica directamente en un esquema de control automático, sino que se ofrece al operador y éste decide en última instancia su aplicación. Por la manera como es empleada la información generada, la estrategia toma en cuenta las limitaciones y las costumbres de los operadores. Las pruebas en simulación llevadas a cabo muestran la factibilidad de la estrategia y el buen desempeño que se obtiene a través de la aplicación de cualquiera de las tres variantes de control predictivo ofrecidas.

Palabras Clave: Control predictivo, optimización, ANFIS, modelo auto-regresivo, generador de vapor, central termoeléctrica.

1 Introduction

Improvement of the operations at the fossil power plants is a constant concern of all instances involved in the process of power generation because increase in production means increased financial benefits and general well-being. Essentially, the heating process of the steam generator at a fossil power plant is a problem of control. Traditionally this problem is solved manually by experienced operators. The main technical difficulty for an automatic control at the startup stage at these power plants is the presence of a significant transport delay which can cause instability and problems in maintaining the temperature gradients within controlled stages of change.

The conventional predictive control uses lineal prediction models to estimate future output values in the process (Clarke et al., 1987, Sousa et al., 1996). In general, lineal models are not sufficiently representative of the process in the case of non-lineal plants. Non-lineal models based on the physical principles of conservation are too complicated to be used in predictive control schemes and involve high costs in computerization and time. On the other hand, recent developments in artificial intelligence such as fuzzy logic and neural networks offer alternatives for models for non-lineal processes. The fuzzy inference systems (Babuška and Verbruggen, 1996, Jang, 1993, Jang and Sun 1995), as well as the neural networks (Haykin, 1999, Nϕrgaard et al., 2000), have been demonstrated as being universal approximators and therefore they can be used for non-lineal input-output mapping with arbitrary approximation. In this way, the fuzzy inference systems and the neural networks can be used as process models with more acceptable computational costs (Babuška, 1999). A variety of control schemes use this kind of model, such as inverse control, the internal model control and the predictive control based on models (Babuška and Verbruggen, 1996, Norgaard et al., 2000, Narendra and

Parthasarath, 1990). In this paper we develop a variant based on the last scheme, which we have called "predictive control based on an auto-regressive neuro-fuzzy model" (Ruz, 2001, Ruz, et al., 2001), because the model corresponds to a Fuzzy Inference System based on an Adaptable Network (ANFIS) (Jang, 1993, Jang and Sun, 1995) which is capable of auto-regressive execution.

2 Problem Description

During most of the steam generator startup process, the operator must not exceed certain limits in the gradient of the temperature[1] in the downcomers (Kramer, 1954, CFE 1994). The actions at the disposal of the operator to control the heating of the fluid in the steam generator concern the quantity of fuel that is consumed as well as the aperture of the steam drains located along the length of the steam pipes. However, for operative reasons these drains are handled with caution because they are subject to a gradual closure program and preferably should not be used as controls. There are further restrictions at another heating and pressurization stage at the steam generator. These no longer apply to the temperature in the downcomers, but to the difference between the temperature of the main steam and the temperature of saturation in the drum. However, the control is carried out in the same way, by simply diminishing the gradient reference value to a level that, by experience, the superheat is known to be within the limits set by the design. After a certain period of heating, positive pressure readings are registered in the pressure of the main steam. This is another variable which should be considered. There are no real, absolute restrictions on the evolution of this one, but an increase must always be guaranteed. This variable is affected by the position of the drains as well as by the usage of the steam in the heating of the auxiliary steam pipes and the turbine metals.

In the first instance, the problem to be solved can be seen as the control of the internal temperature of the downcomers. The maximum limit of the gradient is an important factor in this variable. If the temperature is greatly reduced, there will be regularly prolonged periods of time in the startup of the steam generator, and this will increase the operation costs due to a higher consumption of fuel, demineralized water and energy from the National Electrical Network. Therefore the faster the heating in the startup process, the lower the consumption of the resources mentioned, but at the same time there is an increase in the thermal stress on the steam generator and, as a consequence, the premature ageing of the pipes. For this reason the operator needs to obtain the fastest possible startup, without exceeding the gradient limits imposed by the design.

With reference to the previous description, the problem that is solved in this investigation is the design and the simulation testing of the feasibility of a control mechanism which allows the estimation of the optimal fuel flow required, taking into consideration the conditions described for this process.

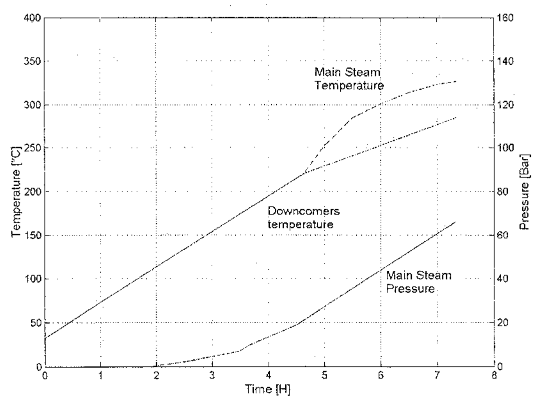

Figure 1: Curves for Heating and Pressurization in the Steam Generator.

3 Development of a Control Algorithm

In order to solve the problem presented, a predictive control algorithm based on an auto-regressive neuro-fuzzy model was developed. The scheme is shown in Figure 2 and involves the use of neuro-fuzzy identification to obtain an auto-regressive model from empirical data on temperature and fuel flow involved in the startup process of the steam generator. The predictive model will be used in an optimal control strategy to link the problem of numerical optimization with the operational limitations of the technical problem explained above. The principles on which our control algorithm is based are the same as those of the Generalized Predictive Control in (Clarke et al. , 1987), except that we use a non-linear ANFIS model instead of a linear model. Consequently we should use non-linear numerical techniques to solve the optimization problem.

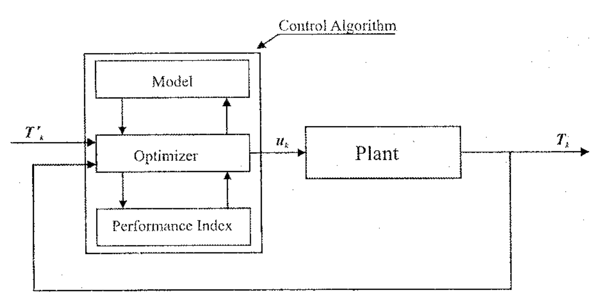

Figure 2: Strategy for Predictive Control Based on an Auto-Regressive Neuro-Fuzzy Model.

[1] Temperature gradient is the temperature change rate

3.1 Development of the Model

In our case, the neuro-fuzzy identification was obtained by using an ANFIS type system with a dimension 2 regressor; 4 membership functions of the Gaussian type for each input; and 4 rules of the Takagi-Sugeno type (Takagi and Sugeno, 1985), which requires the estimation of 16 antecedent parameters and 12 consequent.

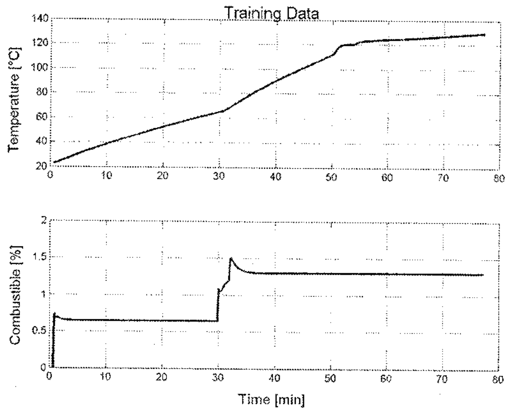

Figure 3: Input-Output data used to train an auto-regressive neuro-fuzzy model.

For this purpose, several tests were run using two tables with experimental data obtained from two independent tests. The data was obtained using 10-second sampling intervals, every test being initiated at the startup of the fossil power plant. The data in the first table, plotted in Figure 3, was used to train the ANFIS model. The data in the second table, plotted in Figure 4, was used to validate the ANFIS model. Different candidate feedback inputs were tested in order to find a model to fit an auto-regressive scheme as shown in Figure 7.

This selection criterion for the inputs is simple and produced satisfactory results (Jang, 1996). During the training, the antecedent and consequent parameters were synchronized according to the Algorithm of Hybrid Learning which combines the Back Propagation Rule and the Least Squares Estimator to finally select those that give the least test error (Jang, 1993, Jang, 1995). Only 3 epochs were required to obtain an acceptable model.
The expression that defines the network which achieved the best results in the training using a parallel scheme (nonauto-regressive) has the following structure:

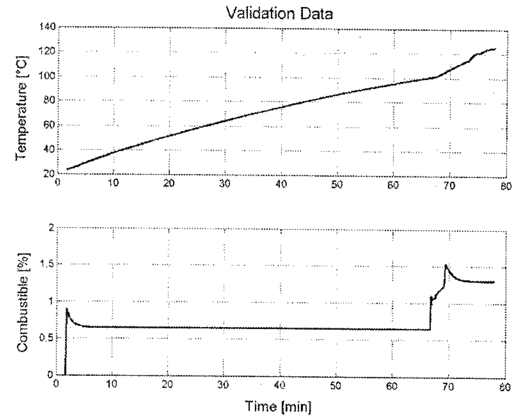

Figure 4: Input-Output fresh data used to validate the obtained auto-regressive neuro-fuzzy model.

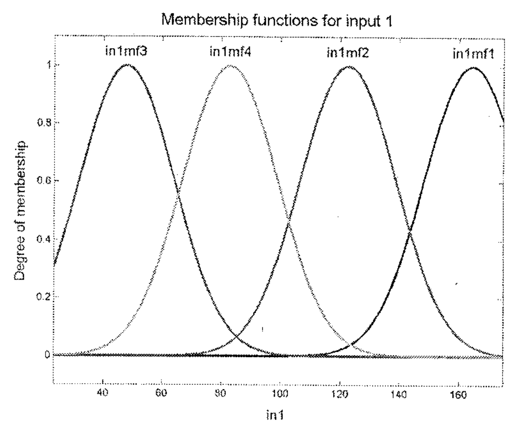

Figure 5: Membership functions to input 1.

$$\hat{T}(k) \approx f(T_{k-1}, u_{k-3}) \qquad (1)$$

where:

$\hat{T}(k)$: Predicted value for the temperature in °C at the sampling instant *k*.

T_{k-1} : Plant temperature in °C at the sampling instant $k-1$.

u_{k-3} : Value for the fuel flow in M^3/H in the sampling interval *k-3*.

Subsequently, the model was tested in a series-parallel scheme, to test the capacity of the auto-regressive version. As a result the model acquires the following structure:

$$\hat{T}(k) \approx f(\hat{T}_{k-1}, u_{k-3}) \qquad (2)$$

where the symbols have the same significance as those above (the hat represents predicted values).

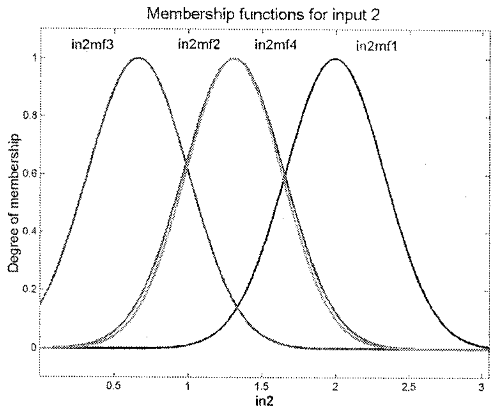

Figure 6: Membership functions to input 2.

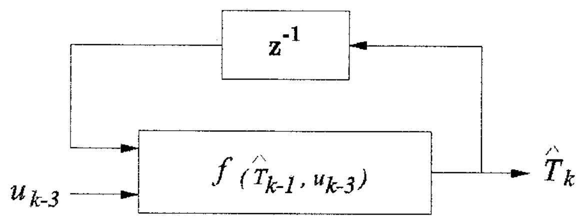

Figure 7: Auto-regressive neuro-fuzzy model for a 10-second sampling period

The obtained ANFIS model is defined by:

- The input 1 membership functions depicted in Figure 5.
- The input 2 membership functions depicted in Figure 6.
- The consecuent parameters given in Table 1.
- The following four rules of the Takagi-Sugeno type: If in_1 is in_1mf_i and in_2 is in_2mf_i then out_1 is mf_iout_1 where $i=1, \ldots, 4$.
- The input-output relationship described by (2) and shown in Figure 7.

The comparison between the data on the temperatures at the plant and the approximations with the auto-regressive model is shown in Figure 8 by continuous and dashed lines respectively, where it can be observed that both are almost superimposed. This signifies that the model appropriately represents the plant and can therefore be used to predict the behavior of the plant required by the control algorithm.

3.2 Numerical Optimization Applied to the Control Synthesis

Concerning the problem of numerical optimization, the following principal points were taken into consideration:

- Given that the operator has a numerical display showing precision to a decimal, the fuel flow used in the optimization to determine the optimal fuel flow should be a multiple of:

$$\Delta = 0.1 M^3 / H \tag{3}$$

- The interval from which the values for the variable of volume fuel flow are taken is:

$$0 \le u_k \le 10\, M^3 / H \tag{4}$$

- There is no existing mathematical model based on physical principles for the process to be controlled, neither are the derivatives known and therefore the properties are unknown. We only have experimental data on the subject with which we have constructed an auto-regressive neuro-fuzzy.

Coefficient Input 1	Coefficient Input 2	Independent Term
0.9956	0.0916	0.6150
0.9956	0.0916	0.6150
0.9967	-0.0538	0.4156
0.9878	0.1359	1.1960

Table 1: Consequent parameter of the ANFIS model obtained.

We also need to consider the following existing operative conditions in order to develop the control algorithm that can be applied to any fossil power plant with similar characteristics to those we have identified:

- The control signal u_k will remain constant for 10 minutes.
- Every ten minutes the operator will take a reading of the temperature of the plant.
- The control signal will be updated every 10 minutes.
- The operator will close the control loop every 10 minutes.

Three operational variants were tested for numerical optimization and are described below.

3.3 First Optimization Variant

This involves determining the optimum fuel flow u_k, under the conditions described in the previous section, to minimize the following performance index:

$$\begin{aligned} J(u_k) &= \alpha_k (\hat{T}_{k+H_p+d-1} - T^r_{k+H_p+d-1})^2 \\ &+ \beta_k (u_k - u_{k-1})^2 \end{aligned} \tag{5}$$

where:

$\hat{T}_{k+H_p+d-1}$: Predicted temperature in °C for the instant H_p+d-1 sampling periods subsequent to the instant k.

$T^r_{k+H_p+d-1}$: Temperature reference in °C at the instant H_p+d-1 sampling periods subsequent to the instant k.

u_k: Optimal fuel flow in M^3/H to be applied in the following $Hp+d-1$ sampling periods.

u_{k-1}: Fuel flow applied to the plant during the previous $Hp+d-1$ sampling periods.

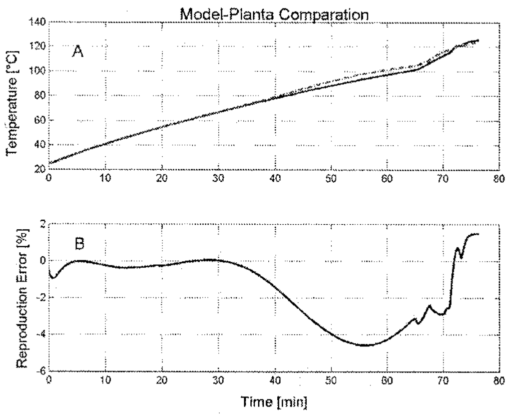

Figure 8: Comparative Graphs: (A) the approximation obtained from the auto-regressive neuro-fuzzy model (dashed line) and the output temperature of the plant (continuous line) in °C. (B) the model reproduction error as a percentage of the plant temperature at any given moment.

α_k: Scalar corresponding to the weight of the quadratic error of the temperature.

β_k: Scalar corresponding to the weight of the control effort.

Hp: Prediction horizon in sampling periods.

d: transport delay in sampling periods.

Note that $u_{k+Hp+d-1} = \ldots = u_{k-1}$, and $d=3$ according to the obtained model.

This performance index contains two terms, the sum of which should be minimized. The first is the square of the error of the predicted temperature at the end of a prediction horizon of $Hp+d-1$ sampling intervals, whilst the second is the increment inthe control action. Both terms will be weighed with the factors α_k and β_k, respectively. The error is defined as the difference between the predicted temperature and its reference value. The minimization of the first term aims at reducing the temperature tracking error, whilst the second term aims at reducing the cost of the applied control. The different usages of the factors α_k and β_k aimed at testing the weight of the terms in the cost function which is to be optimized. In this way a high value in α_k signifies that to achieve the result more importance is given to the reduction of the tracking error than to the cost, whilst a high value for β_k signifies that cost is more important to achieve the objective than the resulting error. Therefore, α_k and β_k are design parameters and a compromise between both factors should be achieved in order to obtain a good performance of the control. It should be observed that the performance index is evaluated using the value of the predicted temperature at the end of the interval during which the control is maintained as a constant; the intermediate values are not considered here. In this way, if the temperature deviates considerably at intermediate points in the prediction interval but finally has a value similar to the reference, the index will show a low value, which could be a disadvantage if the control variable fluctuated around the regulation values.

The prediction horizon Hp in the performance index (5) is a design control parameter and should be adapted to the actual operating conditions at the fossil power plants. In this application, the control signal will be updated every 10 minutes, thus Hp will be selected to be approximately 60. With a 10 second sampling period, 60 sampling periods will total 10 minutes. Simulation tests can be run to select the best option.

In order to minimize the performance index (5), a search is carried out to determine the optimal fuel flow. This is achieved using a procedure of varying the fuel flow according to the equation (3) in the interval given in (4) and evaluating it in the performance index in such a way that, by comparing each evaluation, the fuel flow necessary to minimize the equation (5) can be determined. It is necessary to make $Hp+d$ predictions because in the case of (5) we need to find out $\hat{T}_{k+H_p+d-1}$, whereby evaluating the auto-regressive neuro-fuzzy model. The initial $d-1$ predictions involve the known fuel flow from the previous Hp periods.

$$\begin{aligned} \hat{T}_{k+1} &= f(T_k, u_{k-1}) \\ &\vdots \\ \hat{T}_{k+d} &= f(T_{k+d-1}, u_{k-1}) \end{aligned} \tag{6}$$

where:

T_k: is the plant temperature in °C at the instant k.

$\hat{T}_{k+1}$: where $i=1, \ldots, d$ are the predicted temperatures involving the previous fuel flow u_{k-1}.

Once the initial predictions have been carried out, we must calculate those in which the optimal fuel flow to be applied during the period should be determined according to the optimization procedure:

$$\begin{aligned} \hat{T}_{k+d+1} &= f(T_{k+d}, u_k) \\ &\vdots \\ \hat{T}_{k+H_p+d+1} &= f(T_{k+H_p+d-2}, u_k) \end{aligned} \tag{7}$$

Note that the optimum combustion flow to be determined is stated as u_k because the quantity of fuel used during the first d predictions is known, and corresponds to the result of the previous optimization. These predictions should be done iteratively for each variation in the combustion flow every 10 minutes during the generator startup process.

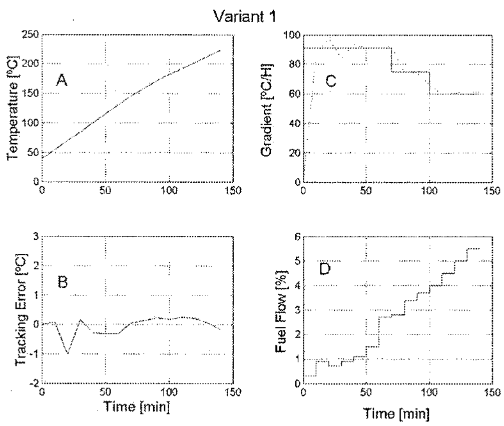

Figure 9: Simulation results for testing the Variant 1. Note that in Graph A the temperature and its reference are overlapped, and in Graph C the gradient is depicted by a dashed line while its reference is depicted by a continuous line.

3.4 Second Optimization Variant

This consists in using the performance index of Variant 1, given in the equation (5), but the restriction of finding the minimum usage of fuel u_{k-} that maintains the controlled temperature below the given reference, has been added.

The aim of proposing this constraint is to indirectly find an improved regulation of the temperature gradient using the supposition that by maintaining the temperature below that of the reference, the control stress will be less and as a result the gradient will not have marked changes.

It is possible that there is no minimum for this situation. However, if this should be the case, the fuel required will be calculated on the basis of the first variant, although the controlled output will be reasonably above the reference at a minimum distance. We will denote the fuel needed in these cases as u_{k+} . The restrictions can be written in the following way:

We first define

$$U_{k-} = \left(u_k / T^r_{k+1} - \hat{T}_{k+1} \geq 0 \right) \qquad (8)$$

$$U_{k+} = \left(u_k / T^r_{k+1} - \hat{T}_{k+1} < 0 \right) \qquad (9)$$

From which we should note

$$U_{k-} \cup U_{k+} = U_k, \quad U_{k-} \cap U_{k+} = \phi \qquad (10)$$

where ϕ is the empty set.

Accordingly, the optimal fuel to be used will be calculated in the following way:

$$u_k = \begin{cases} u_{k-} / J(u_{k-}) = \min J \text{ and } U_{k-} \neq \phi \\ u_{k+} / J(u_{k+}) = \min J \text{ and } U_{k-} = \phi \end{cases} \qquad (11)$$

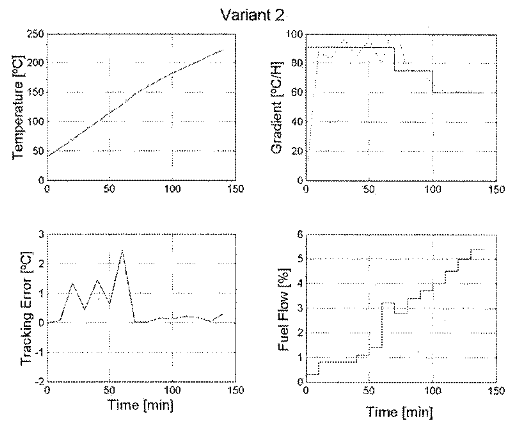

Figure 10: Simulation results for testing the Variant 2. The positions and types of lines correspond with those in Figure 9.

3.5 Third Optimization Variant

The two previous variants minimize a cost function that does not involve temperature deviations corresponding to intermediate samples at 10 seconds in each period of 10 minutes. Therefore we will now use the following:

$$J(u_k) = \frac{1}{H_p} \sum_{j=d}^{Hp+d+1} \alpha_k \left[\hat{T}(k+j+1) - T^r(k+j-1) \right]^2 + \beta_k (u_k - u_{k-1})^2 \qquad (12)$$

where the symbols have the same meaning as described above.

Note that here this performance index corresponds to an average of *Hp* evaluations of the performance index (5) at the sampling instants. The samples $j=1, \ldots, d-1$ have not been considered, because the fuel usage for determining u_k is not included here, as this information is available from the previous period u_{k-1}.

This performance index is more standardized in the literature on predictive control. As this deals with the average of the performance index of Variant 1 and to some extent also of Variant 2, it is expected that there will be a better performance of the control obtained by optimization although the computational cost is higher than the evaluation of the other indexes.

4 Simulation Results

This section contains the results obtained from the simulation of the predictive control scheme shown in Figure 2 and for the different variants of the optimization procedure described in the previous section, using the auto-regressive neuro-fuzzy model as a predictor as well as a plant in the scheme.

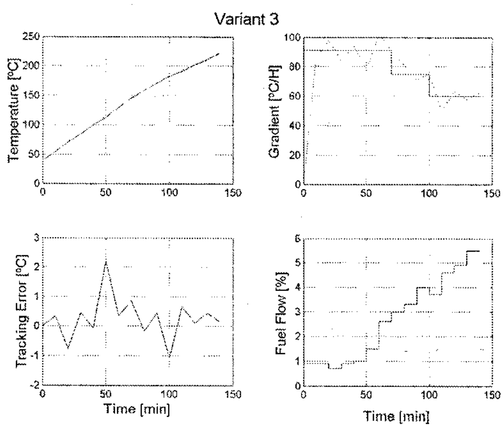

Figure 11: Simulation results for testing the Variant 3. The positions and types of lines correspond with those in Figure 9.

The value of α_k at every instant k in the three optimization variants is 1. The value of 0.1 is assigned to β_k at every instant k in the first and second variants. In the third variant the value of β_k is 0.01 at every instant.
In all cases, the simulation tests were carried out by programming the control algorithm in MATLAB for a startup with a reference signal of the conventional temperature shown in Figures 9-11. With this reference an initial startup gradient of 90°C/H, descending to 75°C/H, down to 60°C/H is sought after.

The results obtained with the three variants are similar. The temperature tracking curves, in all cases, almost overlap with the temperature reference, Graphs A in Figures 9-11. At the changes in gradient reference, we can observe slight increases in the tracking error. The fuel consumption is similar in all cases. In the some way, the curves representing the behavior of the gradient show a clear tendency to be the same as those of the gradient reference, with slight deviations within acceptable operational limits.

5 Robustness Tests

Random noise with gaussian distribution average 0 and variance 1 was added to the original predictive control scheme shown in the previous section, with the aim of simulating errors in the measurements of temperatures taken in the plant, Figure 12.

Given that the control algorithm is based on an auto-regressive neuro-fuzzy model that provides temperature predictions, the random noise is propagated through the same channels. This procedure serves as a test for the robustness of the constructed algorithm because the optimization routines that were used will determine the fuel flow at each updating stage. In the case of the previous simulations, the robustness test demonstrate the same tendencies observed in the three variants, as can be seen in Figure 13-15, which corresponds to the control algorithm for the variants 1-3, respectively.

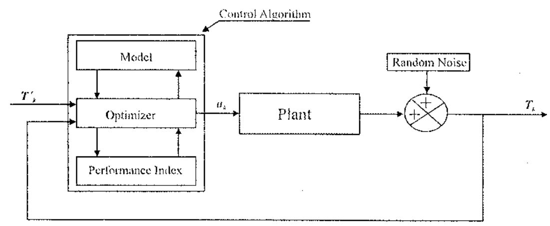

Figure 12: Proposed Scheme to Test Robustness.

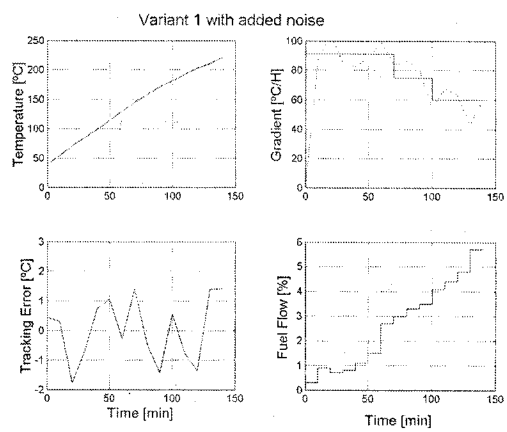

Figure 13: Simulation results for testing the Variant 1 with added noise. The positions and types of lines correspond with those in Figure 9.

6 Analysis of the Results

According to the previous graphs the tracking of the temperature reference is adequate in all the variants, even when random noise is added to the measurements. We can see that the temperature tracking error increases when the change rate in temperature descends to 60 °C/H, which causes transient instability in the behavior of the gradient. In the case of the proposed optimization variants it was observed that the control algorithm provides us with the fuel flow to be used by the operator for each period. This achieves a temperature tracking reference with very small deviations. The robustness test applied to each of the variants showed that in some fuel update periods the error increases but in small degrees, and that they consequently have little effect on the temperature tracking. This indicates that the temperature control of the fluid transported in the downcomers is adequate.

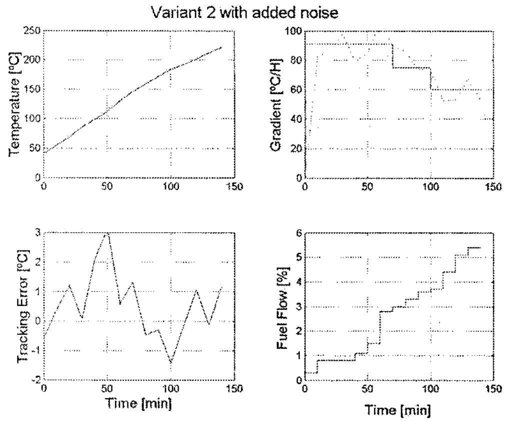

Figure 14: Simulation results for testing the Variant 2 with added noise. The positions and types of lines correspond with those in Figure 9.

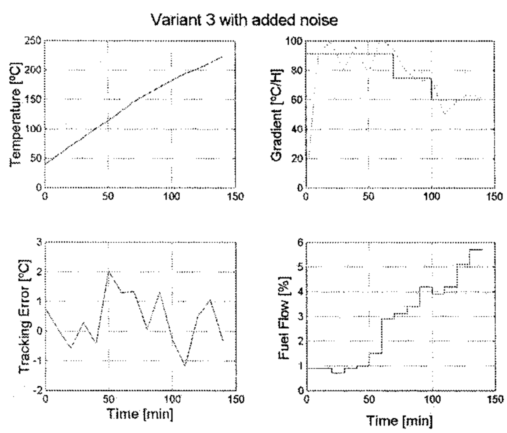

Figure 15: Simulation results for testing the Variant 3 with added noise. The positions and types of lines correspond with those in Figure 9.

7 Conclusions

From these results we can observe that the control algorithm that has been developed fulfills the principal design requirements to solve the problem and furthermore it can be applied to the different fossil power plants in the country. The neuro-fuzzy identification demonstrated the efficiency of this type of technique to easily obtain from the data reliable models of the process, and that they are useful as predictors in control predictive schemes based on the model. It is possible to improve the behavior of the temperature gradient by adding a third term which participates in the performance index to be minimized.

A control scheme based on an auto-regressive neuro-fuzzy model is provided and this represents an improvement in the operation of the fossil power plants.

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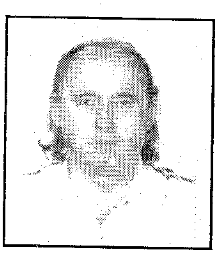

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