Feedback-Error-Learning in pelletizing plant control

Paulo Rogério de Almeida Ribeiro[1], Tarcisio Souza Costa[1], Victor Hugo Barros[1], Areolino de Almeida Neto[2], Alexandre César Muniz de Oliveira[3]

[1]Ciência da Computação – Universidade Federal do Maranhão (UFMA)
65.085-850 – São Luís – MA – Brasil

[2]Departamento de Engenharia de Eletricidade – UFMA

[3]Departamento de Informática – UFMA

pauloribeiro1000@yahoo.com.br, {priestcp,bs.victorhugo}@gmail.com

areolino@ufma.br, acmo@deinf.ufma.br

Abstract. *This work is devoted to present a process control application in an industrial process of iron pellet cooking in an important mining company in Brazil. This work uses an adaptive control in order to improve the performance of the conventional controller already installed in the plant. The main strategy approached here is known as Feedback-Error-Learning (FEL), in which a neural network (NN) learns to improve the control actuation of a Proportional-Integral-Derivative (PID) controller. The advantage of the FEL strategy is to provide cooperation between the adaptive controller and the conventional controller, in order that the NN learns not only the actuation necessary for the control, but new actions can be acquired as consequence of changes in the process. A second control strategy is also employed as alternative for the conventional PID control: a Proportional Integrative Logic Fuzzy Controller (PI-FLC). Fuzzy controllers have been satisfactorily used in presence of non-linearity or absence of a precise mathematical model to address the changes in system state. In this work, due to the unknown mathematic model of the plant and, in order to simulate the control of the process, a neural model of the plant is also presented. In a simulation environment, conventional PID, FEL and PI-FLC strategies are compared and the results are discussed.*

1. Introduction

Vale is one of the world's largest mining companies with operations in production and trade of iron ore, iron pellets, nickel, coal, bauxite and others [Vale]. Vale is a company present in five continents which demand high quality products. Its plant in São Luís, Brazil has a pelletizing plant, which produces iron ore pellets. This plant adds some substances to the iron ore and then puts it in pellet form. At this stage the pellets do not have consistent structure, needing a final cooking.

The process of cooking is performed by 21 burner groups fed with oil. The burner groups are composed of two or four burners, each one controlled by a Proportional-Integral-Derivative (PID) controller. In general, they perform well, except after stoppage or resumption of the process.

This paper shows the results of three process control strategies: a conventional PID, a Fuzzy based controller and the Feedback-Error-Learning control strategy. The later has an adaptive characteristic [AlAli and Sugimoto 2006], i.e. a neural network is added to the control system and acts in harmony with the pre-existing controller. The Artificial Neural Network learns the inverse model of the controlled object.

The use of fuzzy controllers is often justified by the non-linearity or lack of a precise mathematical model to address the changes in system state [Lee 1990]. In general, the rules defining the behavior of a generic controller involve imprecise parameters.

Among the 21 burner groups, one was chosen for the experiments: the burner group number 8. It is believed that the results can be easily extended to the others groups, although there are differences among the groups burners. However the most important is its burning profile, which is set up according to the number of the group.

This paper is organized as follows. In Section 2, the pelletizing process is shown, in order to better understand the production of pellets by the company. In Section 3, the theoretical aspects of FEL and Fuzzy control strategies are presented. Section 4 brings computational results, as well as a comparison between the control approaches. Finally, Section 5 presents the conclusion and directions for further works.

2. The pelletizing process

The pelletizing process is the agglomeration of ultrafine particles of iron ore and additives, including lime, bentonite and other inputs for the production of pellets. It may be noted that the pellets are produced by a technology that allows the recovery of fines generated during the extraction of iron ore, which were previously considered waste. One of the important uses of the pellets is in the production of steel.

The production of iron pellets in Vale's pelletizing plant in São Luís, Maranhão, Brazil can be summarized by Figure 1. This is analyzed from the iron ore in the form of fines, in the courtyard of the fine company to the production of pellets. After pellets are fired, they are ready to be shipped by rail or sea to steel mills in Brazil and around the world.

The cooking of the pellet in Figure 1 is done in an indurate machine, the pellets pass through the 21 burner groups, which form a burner oven, each group provides a fixed value of temperature for a specific profile. The temperatures are between 825.6 °C and 1350 °C. The combination of the temperature of each group is called of burning profile. The burning profile is determined according to the moisture of the pellets and the temperature of each group increases according to the number of the group. The fuel used to cook the pellets is mineral oil, whose purpose is to produce heat.

Since there is a process involved, there are machines, procedures, and men involved in this task. Thus, the cooking of the pellets is based on a system of automated control of temperature, controlled by PID controllers.

3. Control Strategies

3.1. Conventional feedback controller

The Conventional Feedback Controller (CFC) is a servomechanism frequently used in industrial processes. Its main characteristic is robustness. Normally, the CFC is a PID type controller. The PID controller is defined by so called PID gains: proportional (Kp), integrative (Ki) and derivative (Kd) gain. The law of the PID control is in equation 1:

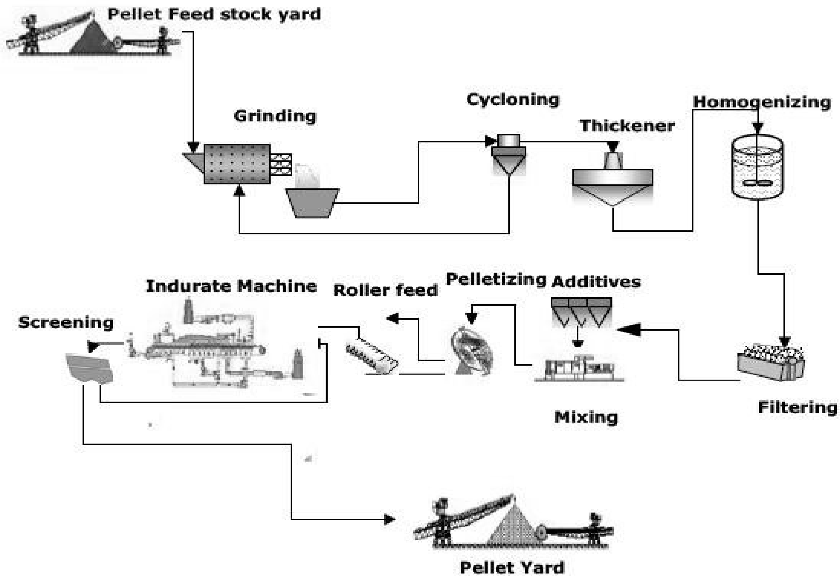

Figure 1. Pelletizing process flowchart(Adapted from [Vale])

$$U_{cfc}(t) = K_p e(t) + K_i \int e(t)dt + K_d \frac{de(t)}{dt} \tag{1}$$

where $e(t)$ is the error measured in an instant of time t, calculated by the differences between the value of the manipulated variable (output of the process) and the reference. The PID works leading zero for this error.

In the control problem presented in this paper, the output of the controller is an electrical signal that activates a valve, expressing the level of openness (0% to 100%), through in which the oil goes. The output of the plant corresponds to a value of temperature in °C.

3.2. Artificial Neural Networks

The Artificial Neural Networks (NN) are inspired by the biological neuron, and composed by a set of artificial neurons. The neural network-based learning methods can be supervised or not. The supervision is characterized by the presence of a supervisor, who indicates the correct output or an idea of output quality of the network. With non-supervised learning, the network tries to group outputs, whose inputs are similar. The most common type of NN is the supervised Multilayer Perceptron (MLP), where the neurons are arranged in layers [Haykin 1999].

An NN with a hidden layer is able to approximate any continuous function [Haykin 1999]. The neural network training is characterized by the modification of its parameters (weights) in order to learn the patterns of input provided during the training, while the execution phase provides outputs with no changing in its parameters for any data presented in input layer.

One of the most used algorithms for training MLP network is the so called Backpropagation [Haykin 1999]. Its goal is to minimize the output error function of the NN. It makes use of an input/output set, in which the network learns to do a mapping of input to output. The algorithm has two phases: forward, that produces the output of the network and backward, responsible for doing the backpropagation of error and only used in the training phase, attempting to minimize the neural network output error by the gradient descending method that confronts desired and obtained output.

3.3. FEL control strategy

The FEL control strategy was proposed by Kawato et al. in 1987 as a way to find the inverse model of the controlled plant in real-time[M. Kawato 1987]. The FEL uses a feedfoward neural network online learning a conventional controller actions. Some real-time iterations of the controller process are used for the FEL neural network (FELNN) training, in which the strategy is to learn what actions make the PID controller stable. After training, the feedforward neural network is able to drive in advance, improving the performance of the control.

The CFC can keep the system stable until the system acquires some knowledge of the system in control. Sometimes, this is not enough to stabilize the system during the training of the network, so an appropriate initialization of the FELNN weights allows the training of the network without instability in the plant.

Another important point to be considered is what should be the signal used as output error to be backpropagated for adjusting the weights in FELNN training. The designer should know exactly the inverse model of the plant to determine the more efficient signal, which is a very difficult task. Moreover, if the model could be known, neural networks would not need be employed.

Due to nonlinear characteristics of the plant, satisfactory FEL behavior has been obtained by using the CFC output. The FELNN has its weights adjusted by backpropagation of CFC output running as output error. Minimizing it, the FELNN indirectly minimizes the output error of the plant, and even if any component integrative, $K_i \int e(t)dt$, exists in CFC, in theory [Karplus 2006], the FELNN output can be canceled by it. The FELNN scheme can be seen in Figure 2.

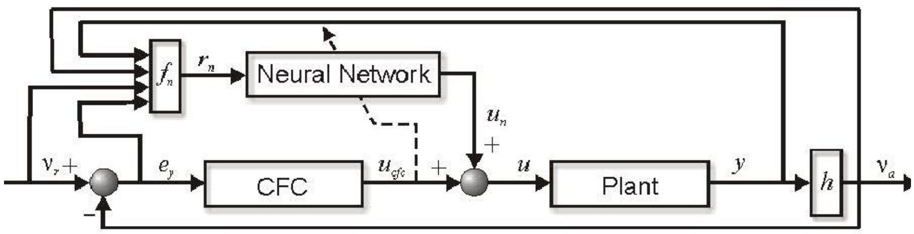

Figure 2. Feedback-Error-Learning scheme

The original FEL scheme was modified by Nascimento Jr. [Jr. 1994] in his PhD studies. The introduced modifications are: feed the FELNN with reference values through a tapped delay line and use the reference signal delayed in the CFC. The first modification of the original Kawato's idea is to provide the variations of the reference signal via delays, instead of use of high order differentiators. The second one provides a delayed reference signal injected into the CFC. This modifications allows the FELNN to learn the delayed inverse model of the plant, which facilitates its job, because the FELNN can know before the CFC any change in the reference signal and therefore provide an anticipating actuating signal to the plant.

One can cite the advantage of the strategy that there is no removal of the existing controller, thus avoiding unnecessary costs with personnel training, because the subsystem is easily coupled to the control loop. This also has the characteristic of being an adaptive control system.

In Figure 2, the added subsystem is an FELNN, but there are other approaches that can be adopted [Neto 2003]. The learning signal is the output of the controller, U_{cfc}, the input signals of the network are free to choose. As we can see in the picture, they are the reference and plant output, respectively.

Assuming the FELNN is an MLP-type network, its error is the output of the CFC (teaching signal), and then the goal of the FELNN is to minimize the action of the CFC, in order to obtain an inverse model of the plant.

3.4. Fuzzy controller

A fuzzy set [Zadeh 1965] is useful when one needs to model sets with ill-defined bounds. The membership function of a fuzzy set A is a mapping: $A : U \rightarrow [0, 1]$, where $[0, 1]$ can be any bounded scale. Fuzzy logic (FL) provides a simple way to deal with ambiguous, imprecise, missing, noisy input information, making qualitative statements, despite such vagueness. FL can be seen as problem-solving methodology applicable when data is ill-defined, but some rules over them are known.

Rules and membership functions can approximate any continuous function to any degree of precision [Mohan and Sinha 2006]. The expertise knowledge can be employed to construct a FLC rather than attempting to model a system mathematically. A control function of a given system can be modeled by a fuzzy rule base and the obtained controller may replace the corresponding PID controller. By your simplicity, fuzzy logic improves control performance, simplifies implementation, and consequently reduces hardware costs.

The fuzzification assigns membership degrees to the system error. The inference machine, based on in production rules, determines the fuzzy output, representing the control actions to be taken by the system. The fuzzy output is, at last, defuzzified for corresponding to adjust (increment or decrement) of percentage of oil to burn.

In this work, PI-FLC is used as alternative in pelletizing plant control. As a conventional PI controller, a PI-FLC can be mathematically represented by 2. The PI-FLC output is not the oil percentage itself, but the positive or negative step for its adjustment.

$$dU_{cfc}(t) = K_p e(t) + K_i \int e(t)dt \qquad (2)$$

In this work, the triangle membership functions are designed for $e(t)$, $de(t)$ and U_{cfc} variables. The defuzzification process, in this work, is based on center of gravity which is so called by considering the output fuzzy sets as a geometric figure over which the centroid is taken as system output.

The fuzzy inference is performed considering control rules constructed from the expertise knowledge over the Plant behavior. The *Fuzzy Associative Matrix* (FAM) is generally employed for representing the rules. Figure 3 shows the 7×7 FAM representing the fuzzy control rules used in this work.

		de						
		PB	PM	PS	ZE	NS	NM	NB
	PB	NB	NB	NB	NB	NM	NS	ZE
	PM	NB	NB	NB	NM	NS	ZE	PS
	PS	NB	NB	NM	NS	ZE	PS	PM
e	ZE	NB	NM	NS	ZE	PS	PM	PB
	NS	NM	NS	ZE	PS	PM	PB	PB
	NM	NS	ZE	PS	PM	PB	PB	PB
	NB	ZE	PS	PM	PB	PB	PB	PB

Figure 3. Fuzzy Associative Matrix

4. Results

The control strategies are now compared against previous Enterprise's PID controller. First of all, the process of modeling the plant is described, followed by the set of experiments that show the effectiveness of the proposed strategy.

4.1. The plant's model

The plant model was obtained by a MLP after a supervised training using a log database of the plant. A neural network was chosen due to possible nonlinearities in the process and due to the absence of any prior knowledge of the system analytical model. The MLP was trained by Backpropagation algorithm over the log database of the eighth burner cluster (burner 8).

Among several MLP configurations we have tested (with or without bias, neurons by layer, etc) the best obtained result was: input layer neurons, 10, hidden layer neurons, 150, and output layer neurons, 1. The MLP input is composed of the history of the controller output (tapped delay line) and the history of the plant. The output of the controller is expressed as a percentage, the flow of oil to burn, released by a valve. The MLP output is a value of temperature in °C. The input data in the interval $[0, 1380]$ was normalized to interval $[-0.5, 0.5]$.

The MLP must be able to generalize the knowledge acquired, or has a small error for data trained and not trained. The log database was pre-processed, filtering signals obtained in the plant setup periods. The plant setup signals do not represent a correct behavior of the plant and hence they shall be discarded from the training database.

The log database was divided into training set and validation set, 65% and 35% of the entire database, respectively. When the mean validation error reached 0.0172, after about $150\ 000$ iterations, the training was stopped.

In Figure 4, the generalization phase, for non-trained data is shown, can be observed that MLP, even for non trained data (test data) obtained a good performance, reaching a good generalization power.

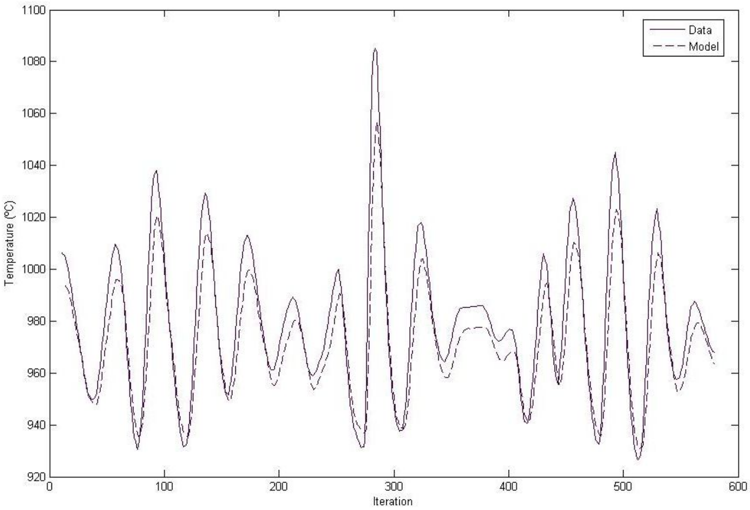

Figure 4. MLP Generalization

4.2. Performace's comparation of controllers

In this section it is shown a performance comparison between PID controller, FEL strategic and Fuzzy controller. The most common set point used in analysis of performance is square wave, which is a standard signal for control analysis. Every simulation was in Simulink and values was exported for MatLab to plot the graphics. The Figure 5 shows a architecture of PID, 6 of Fuzzy and 7 of FEL. The plant represents a burner group, which was simulated by a neural network as detailed in last Subsection, its input is limited, so the cut function provides saturation and its output is burner group's temperature.

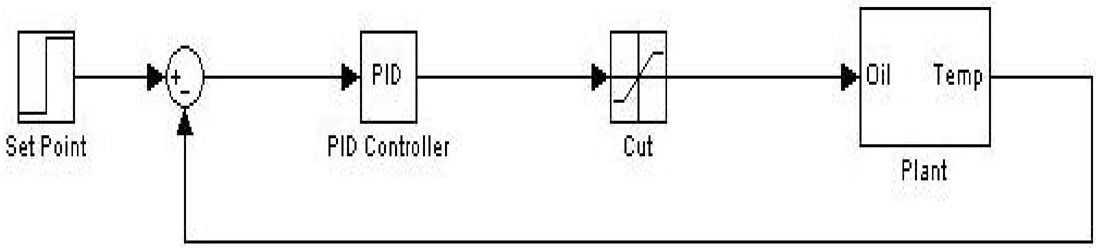

Figure 5. PID

In Figure 5 we can see the input of controller is error signal and output is oil value. The performance is conduct by gains: Proportional(Kp), integral(Ki) and derivative(Kd), equation 1. In Figure 6 shows the scheme of Fuzzy. The Figure 7 shows the input of neural network is composed by set point and signal error.

The main measurement result's analyzes in control are: Overshoot, Up time and Stabilized time. So every simulation were done with same configuration only change the set point. The results for positive edge, negative edge and pulse train are found in Figure 8, 9 and 10, respectively.

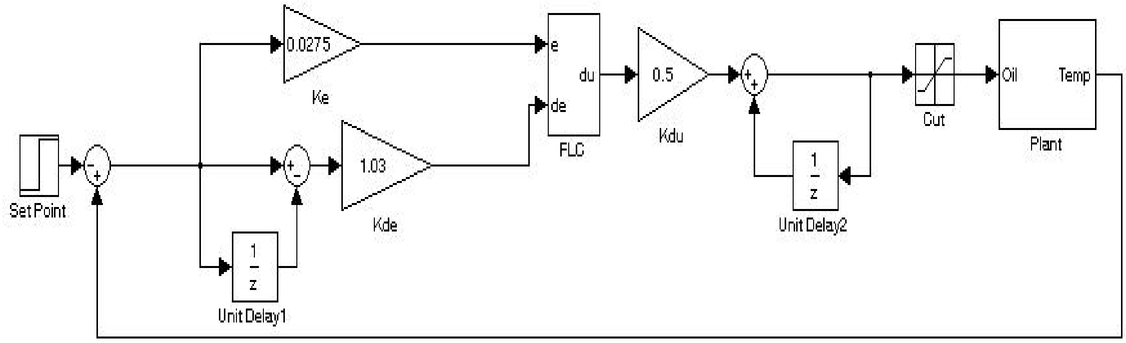

Figure 6. Fuzzy

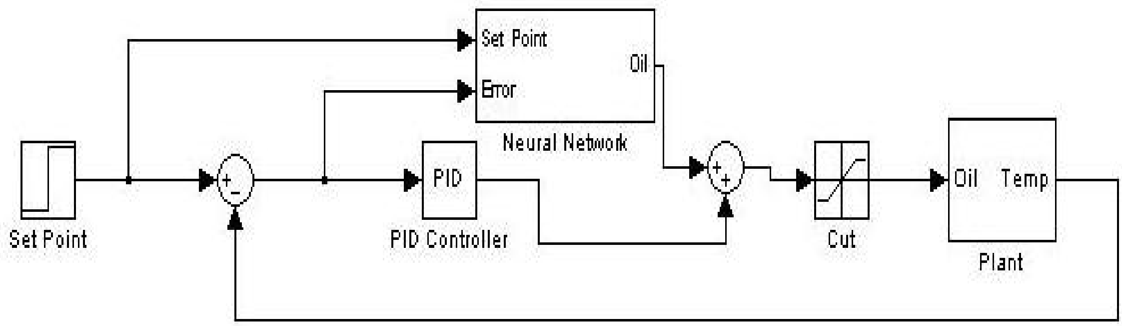

Figure 7. FEL

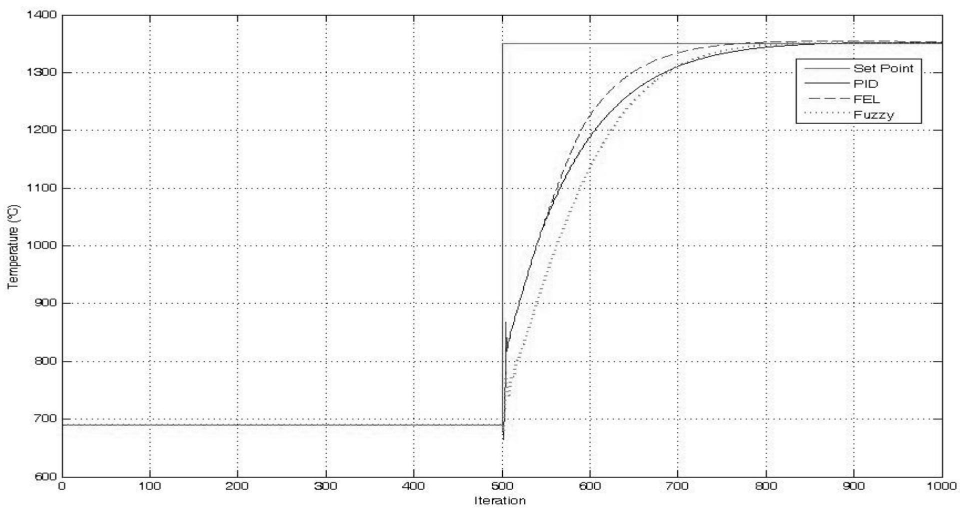

Figure 8. Positive edge

We can observe in figures 8, 9 and 10 the steady-state error of FEL and Fuzzy strategies are quite similar and better than pre-existing PID. However, FEL's response time looks better.

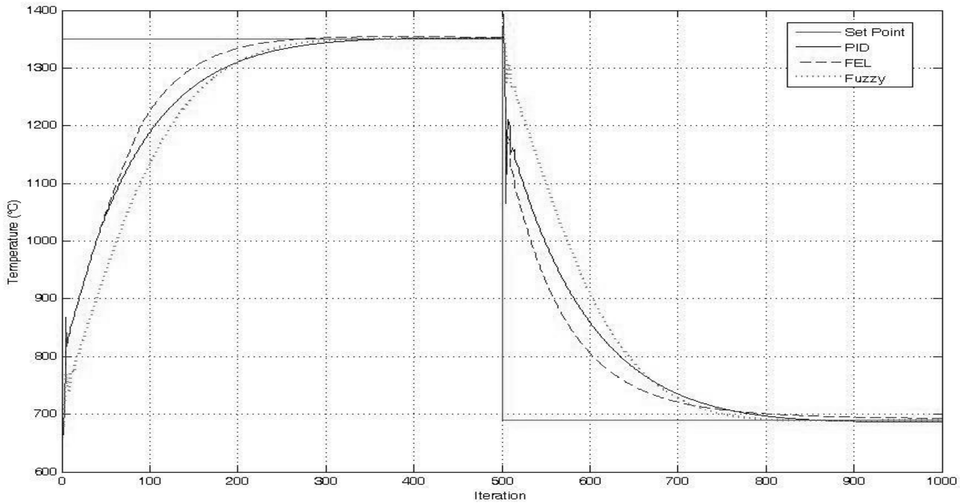

Figure 9. Negative edge

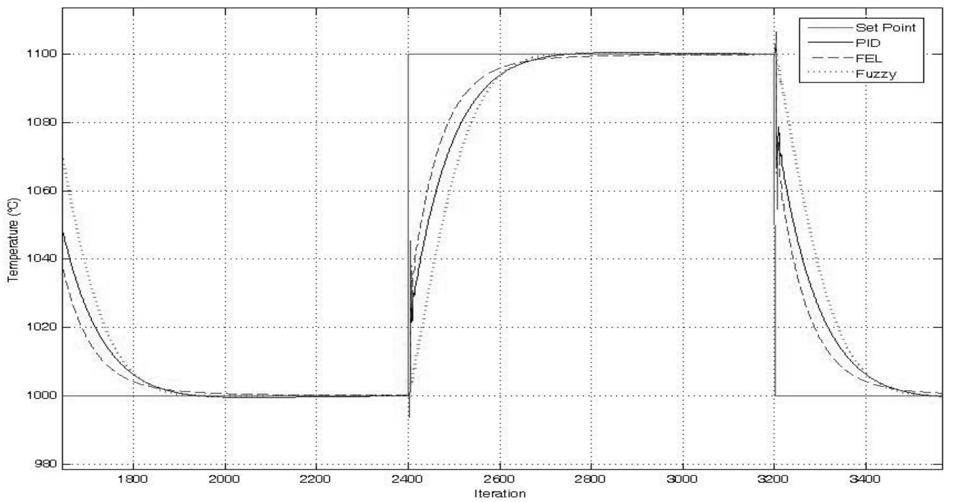

Figure 10. Pulse train

The PID's gain used was: $Kp = 1.5$, $Ki = 0.01$ and $Kd = 0.1$.

Among many tests with different FEL topology and input signals (set point signal, plant output or plant error, plant history), the best neural network: MLP, feedforward and configuration found was $15 - 85 - 1$ for neurons in input, hidden and output layers, respectively. Network's input is a tapped delay line with 14 neurons is a historical of signal error and the actual set point, hidden layer uses hyperbolic tangent function and linear function for output layer. In the training of FELNN it has been preferred to start weights with near-zero or very small values, because in the first iteration unexpected results may occur and the plant could receive large value as input. Another important point is that the FEL training is online, while the plant simulation is performed.

In the Fuzzy controller, input and output variables were defined by symmetric triangular-shaped Fuzzy sets. Each variable contains the following term set: Negative Big (NB), Negative Medium (NM), Negative Small (NS), Zero (ZE), Positive Small (PS), Positive Medium (PM) and Positive Big (PB). Thus, a default FAM with forty-nine rules compounds the qualitative control strategy based on expertise knowledge about plant behavior. The Ke, Kde and Kdu gains were adjusted experimentally to 0.0275, 1.03 and 0.5, respectively.

5. Conclusion

The FEL control strategy was coupled in the pre-existing PID control system in a simulation environment in which the industrial plant is simulated by another neural network that models the industrial process. The FEL control strategy is also compared with Proportional Integrative Logic Fuzzy Controller (PI-FLC), a traditional approach in industrial environment by its simplicity and good performance.

Analyzing the simulation results, the performance of the FEL control strategy showed that is possible to improve the performance of a pre-existing conventional controller adding to the closed loop a neural network. Concerning PI-FLC, FEL control strategy had quite similar performance, but FEL's response time looks better.

For further works, it is planned to investigate other types of FEL control strategy as to coordinate the addition of other neural networks.

Acknowledgements

The authors acknowledge CNPq for the partial support received in the research project "Logística e Planejamento de Operações em Terminais Portuários - PROPOR" (proc. 479762/2006-6), PIBIT, PIBIC, FINEP and Companhia Vale.

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