Neurofuzzy Identification Applied to a Flow Control Equipment

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Abstract. In this paper a neurofuzzy identification scheme is designed for a flow control equipment. The identification procedure includes data collect, Adaptive Neuro Fuzzy Inference System (ANFIS) training and validation with data fresh. ANFIS training is performed online using a Pseudo-Binary Random Signal (PBRS) in order to obtain a neurofuzzy model. The feasibility of the proposed neurofuzzy identification scheme is validated in real time.

Keywords: Neurofuzzy Identification, ANFIS, Flow.

1 Introduction

Numerous advances in science have resulted in new research areas which are modeled on natural behavior of human beings, one of these fields is called Artificial Intelligence, which uses various techniques that mimic the processes of learning, reasoning and making decisions produced in the brain, but applied and directed to objects or systems and thereby provide intelligence. Although this is a relatively new field, since its inception with the contributions of scientists as Lotfi A. Zadeh in 1965 and J. J. Hopfield in 1982 among others, artificial intelligence techniques have been the subject of great interest and now smart devices or systems are in many cases replaces conventional (Ching Tai Lin & C. S. , 1986).

One of the problems for the implementation of automatic control systems is to obtain a model that describes the system dynamics to be controlled. Usually this model is not available or is too complicated for design purposes. Therefore it is important to have a simple model to work with him, but that includes the essential features of the process (Chiasson & Bodson, 1993). Models using neurofuzzy systems are useful to estimate from experimental data where the nonlinearities are included. The ANFIS model allows systems with high nonlinearity and time-invariant which combines the concepts of neural networks and fuzzy logic to form an intelligent system that highlights the ability for adaptation and automatic learning.

2 Description of experimental equipment

The flow measurements have a great importance in the processes and are commonly used for process control and accounting measures (turnover, import / export products), so selecting the best technology has great implication. For example, flowmeters are used to account products within the plant itself, with the outside. As for the process control, flow measurement is essential to perform automatic control and to optimize yields in production units applying material balances for this cause the flow to be measured and controlled carefully (Smith y Corripio, 2010).

In Fig. 1, a block diagram of the interconnected elements used in this work is shown, such as: A PWM voltage regulator module, centrifugal water pump, a flow sensor and data acquisition card DAQ PCI6071E.

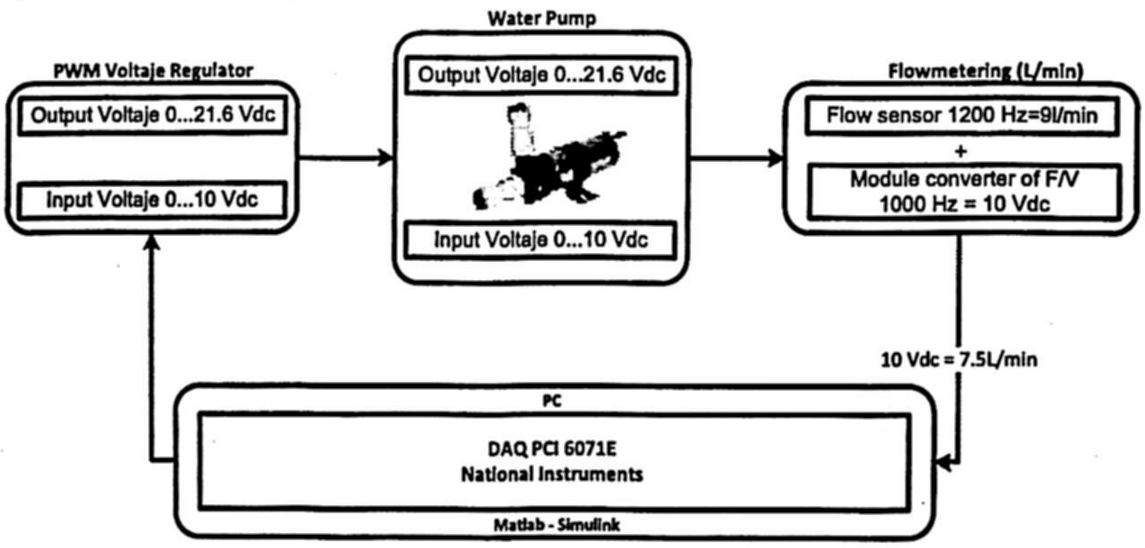

Fig. 1. Block diagram of the connection for flow regulating equipment.

This connection is made to obtain input-output data signals for process.

The pump used in this paper is a centrifugal pump brand Johnson CM30P7-1 model part number 10-24503-04 operates with a 24 Vdc and provides a maximum flow rate of 5 l/min., The module PWM controller brand Kaleja model D-73553 is a DC-DC used to control the voltage applied to the pump drive.

In Fig 2 the flow sensor (IR Opflow Type 2) is shown.

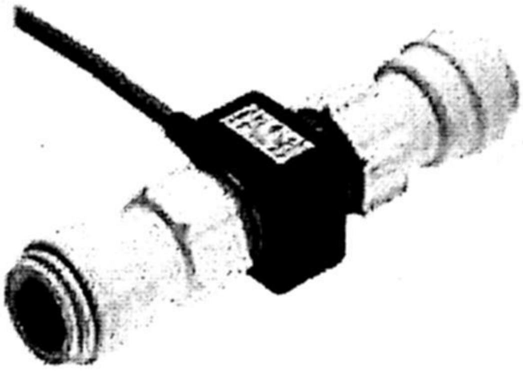

Fig 2. flow sensor (IR Opflow Type 2).

Its measurement range is 0.3-9.0 l / min and the frequency range of 40-1200 Hz output, and a K factor of 8000 pulse/dm3, Equation 1 is deduced.

$$1200\ Hz = 9l/min \qquad (1)$$

The flow sensor has as output signal proportional to the amount of liters per minute making it necessary to use a converter frequency to voltage frequency. By design inverter v/f the maximum input frequency which can be applied to sensor is 1000 Hz by providing at its output 10 Vdc, Equation 2.

$$1000\ Hz = 10\ Vdc \qquad (2)$$

Based on equation (1) and (2) the maximum flow that can be measured are:

$$1000\ Hz \frac{9\ l/min}{1200\ Hz} = 7.5\ l/min \qquad (3)$$

So that the following relationship is obtained:

$$10\ Vdc = 7.5\ l/min \qquad (4)$$

The maximum voltage that the inverter will provide with a flow rate of 5 l/min is:

$$(5\ l/min) \frac{10\ Vdc}{7.5\ l/min} = 6.66\ V \qquad (5)$$

because of this there is no risk of saturation of the sensor and converter.
Fig 3 shows the electrical connection diagram.

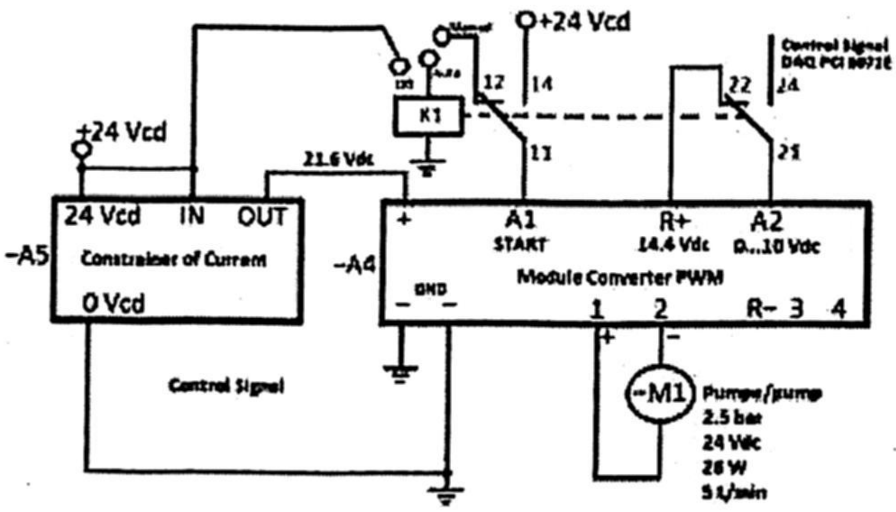

Fig 3. Electrical connection diagram PWM drive module.

3 Data Acquisition

The first step in the identification process is to perform a kind of experiment in the system studied, to collect input-output data are used to obtain the final model. To generate these data the experimental equipment is shown in Fig 4.

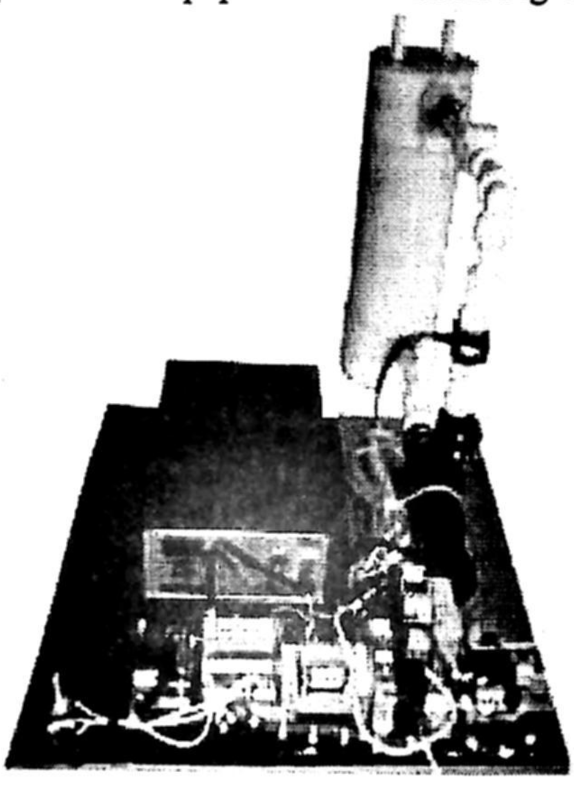

Fig 4. Experimental equipment.

When working with real-time systems, the sampling time also depends on some factors such as processing speed of data acquisition card and runtime model code, and has a decisive influence on the identification experiment.

The selected sampling period is T = 0.01 seconds, the time of data acquisition for this study was 300 seconds obtaining a total of 30000 data which were divided in 15000 for training and the remaining 15000 for neurofuzzy model validation.

Identification scheme used is series-parallel, which is shown in Fig. 5. The error e(k) obtained by the difference between the response of the plant and the identifier is used as a performance index in order to satisfy a set of input-output data in parameter estimation process.

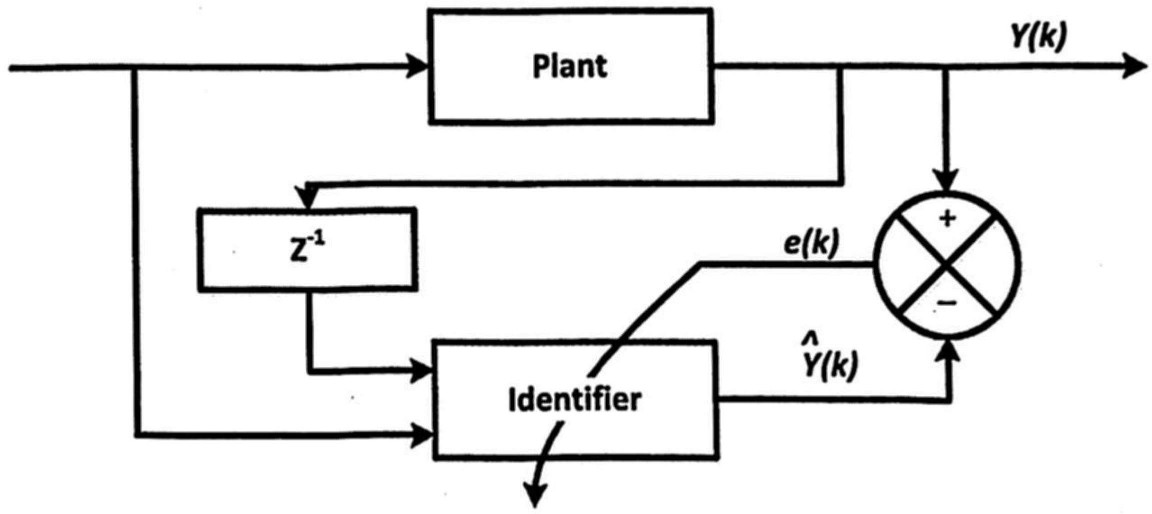

Fig 5. Series-Parallel Identification Scheme

In the data acquisition PRBS was used see Fig 6. For generation of the PRBS a 8 bits shift register with feedback to the first stage of the shift register is used by an exclusive OR operation in the registers 2, 3, 4 and 8, for a period of the sequence of 255.

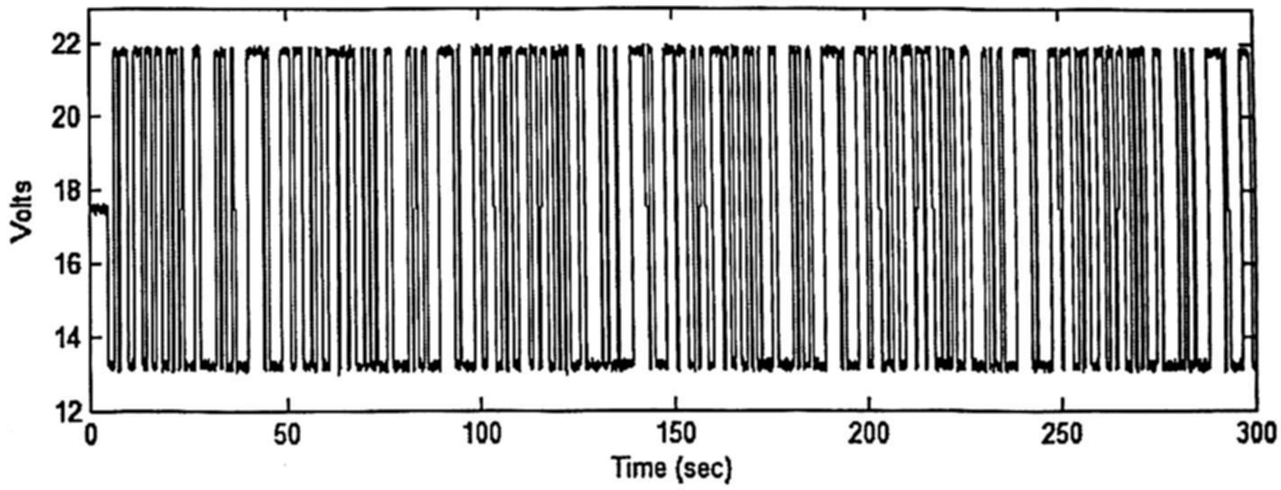

Fig. 6. Pseudorandom binary sequence, signal voltage applied to the pump.

ANFIS have not a recursive structure, past values of the inputs and outputs are used to capture the dynamics plant (Saludes Rodil & J. Fuente, 2007). Previously obtained data from voltage and flow can be used for training tool ANFIS EDIT using Matlab.

Fig. 7 shows the signal from the sensor (l/min.).

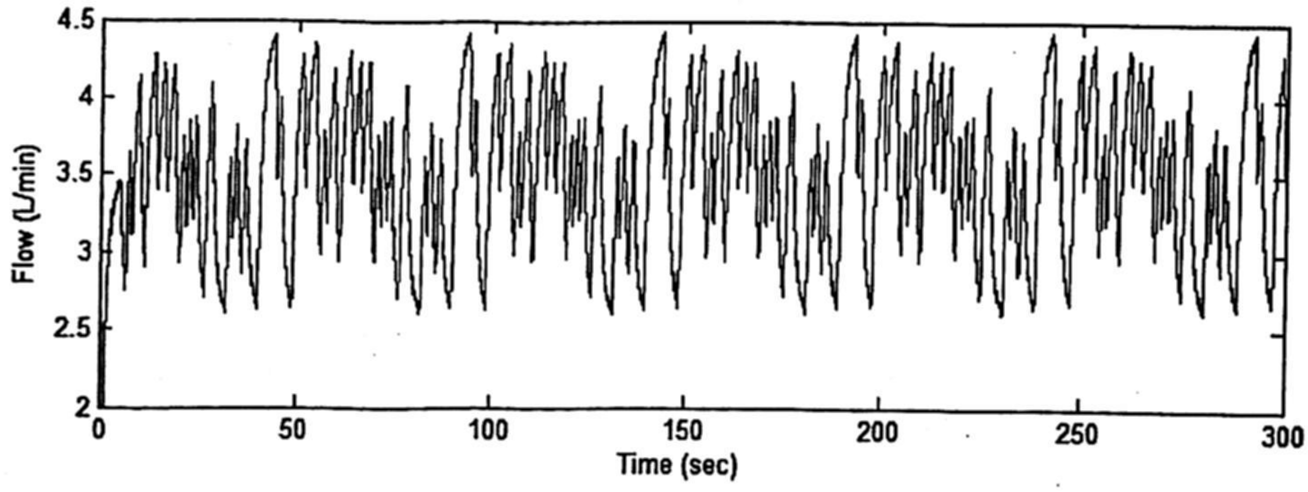

Fig. 7. Experimental data obtained for the sensor.

4 Obtaining model neurofuzzy

The purpose of training is to obtain an elevational tuning neurofuzzy adaptive model adaptive advantage of artificial neural networks, seeking convergence near zero error, this convergence ensures that the model and validate the neurofuzzy be compared to the actual flow output team with the departure of the ANFIS network, the error between the two outputs is close to zero.

In complex systems, it is not always easy to determine the variables that can be used as inputs model, however, through the analysis of dynamic systems is known that for output system at any time $t \geq t_0$, it is necessary know the system at time $t = t_0$ and the system input at time $t \geq t_0$. (Ogata, 1998). Based on this you can determine the inputs that are necessary to perform the routine training ANFIS network of an arbitrary system. In particular you can determine that the team dynamic flow control is completely characterized by the knowledge of the applied variables voltage (V) is the system input and flow rate (Q) is the system output. Thus the flow of equipment at any time $t \geq t_0$ be determined by the knowledge of both the flow and the voltage applied at time $t = t_0$, as well as the flow for time $t \geq t_0$. In other words if you want to find the flow in an instant k+1 is necessary to know the flow rate, applied voltage and k, (Ogata, Control Systems in Discrete Time, 1996). According to the above we can write:

$$Q(k+1) = f\big(V(k), Q(k)\big) \qquad (6)$$

The flow rate Q at time k can be represented as:

$$Q(k) = f\big(V(k-1), Q(k-1)\big) \qquad (7)$$

In the Toolbox ANFIS EDIT, the hybrid learning algorithm and fuzzy inference system (Takagi-Sugeno) T-S 5 membership functions for the Gaussian bell input into the layer 1, the hybrid learning algorithm and the consequent used T-S type fuzzy rules in layer 4. In Fig. 8 the structure for ANFIS network is shown.

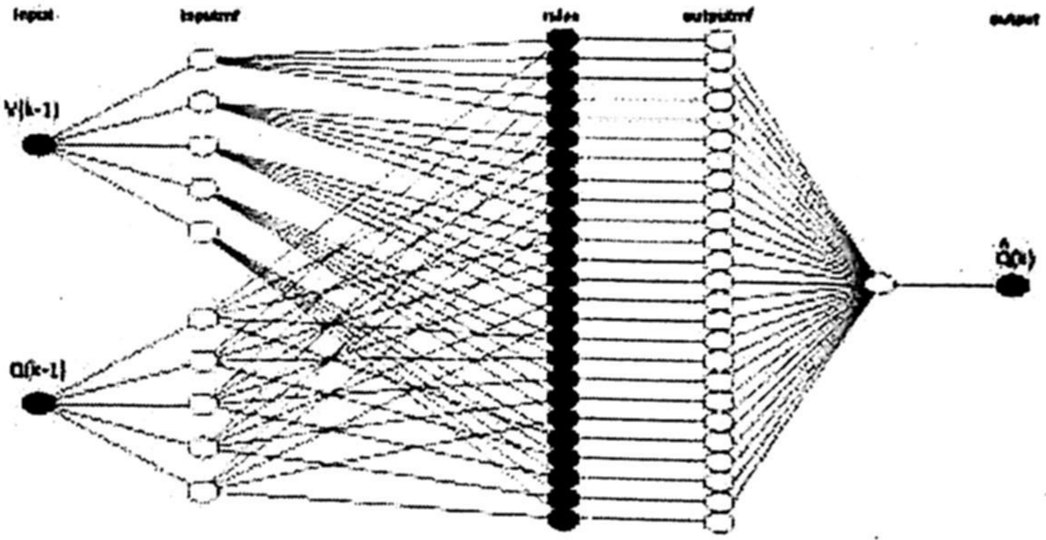

Fig. 8. Structure for neurofuzzy ANFIS Model.

In Fig. 9 neurofuzzy response model validation data is shown. It can be seen total convergence between actual output data of the plant and the neurofuzzy model.

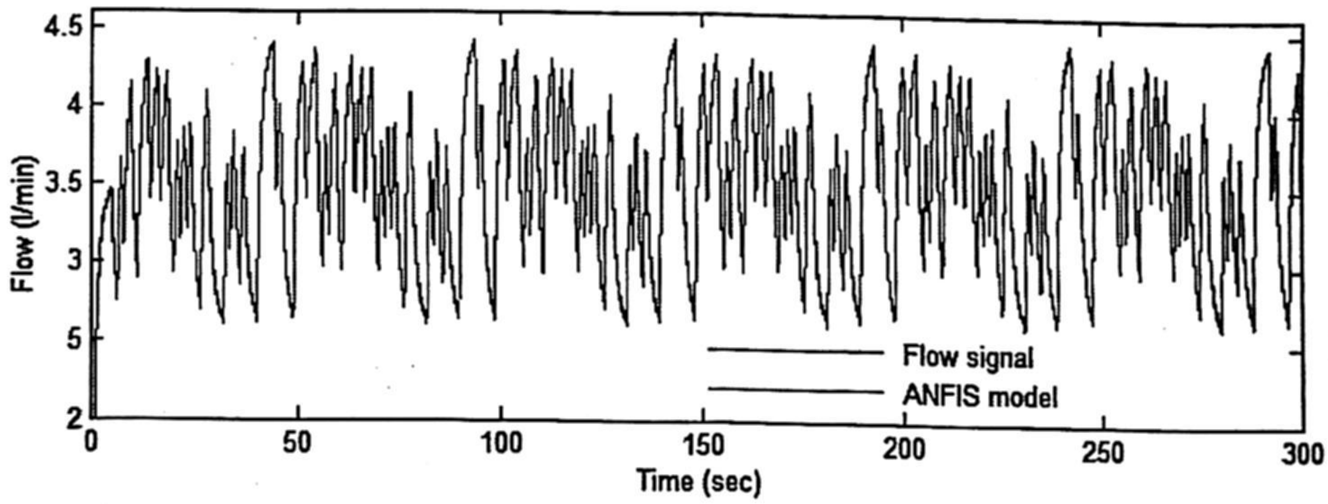

Fig. 9. Neurofuzzy model validation.

In Fig. 10 the prediction error between the neurofuzzy model and the plant is shown.

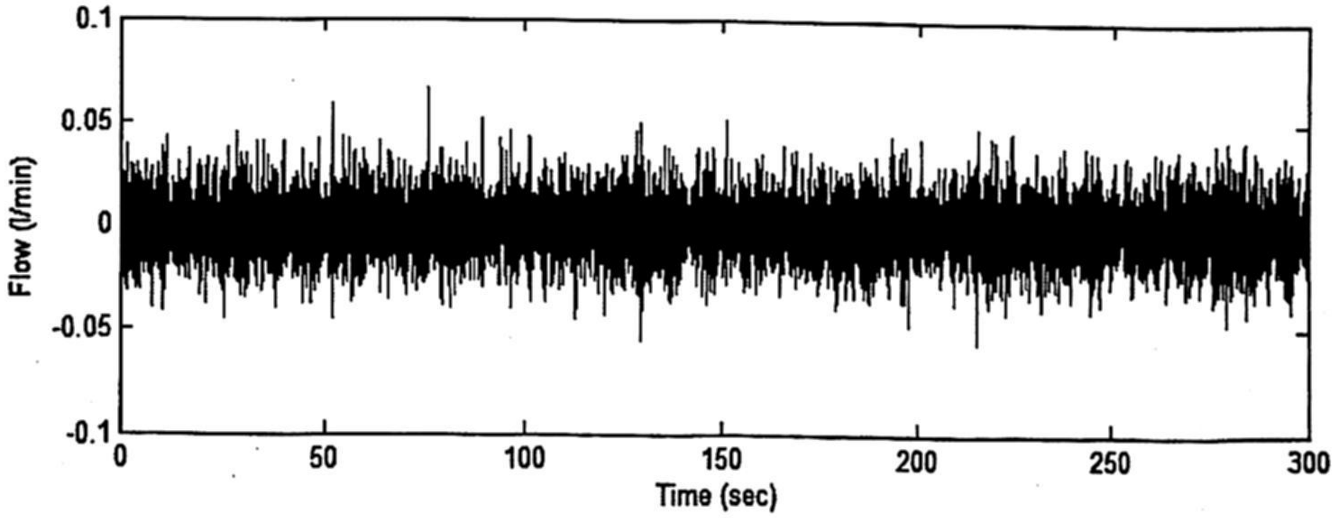

Fig. 10. Prediction error e(k).

5 Real-time validation

For real-time validation a sinusoidal reference signal is applied. The flow signal and estimated flow are shown in Fig. 11.

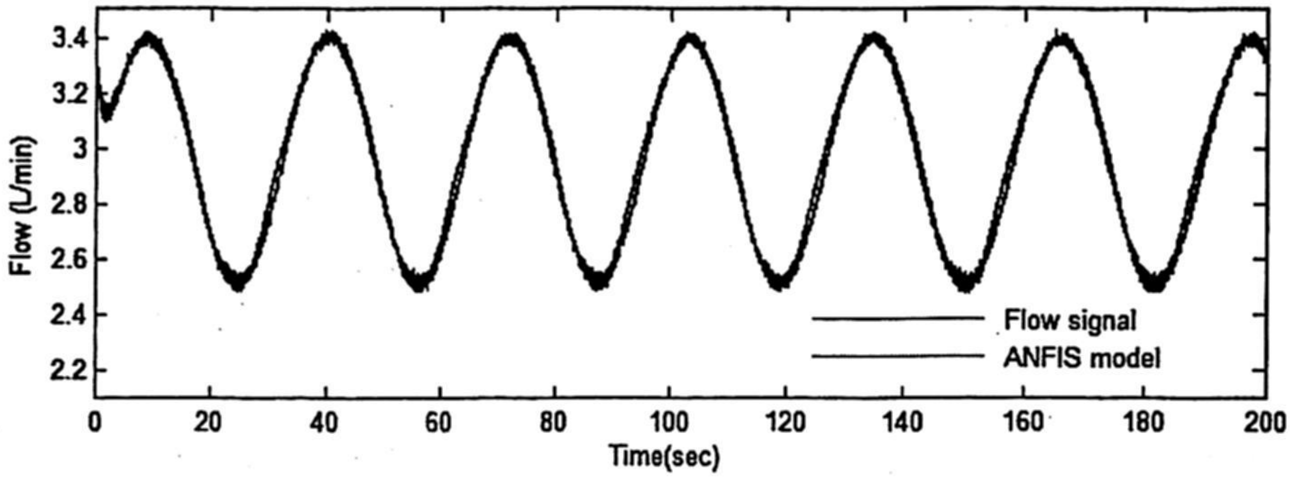

Fig. 11. Flow signal and estimated flow in real time.

6 Conclusion

The proposed neurofuzzy identification scheme was validated in real time using a flow control equipment. For process modeling is very useful to use the technique of Neurofuzzy identification due to it gives very good much information about the system. This technique is based on obtaining data directly from the computer through sensors.

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