Neuro-Fuzzy Controller in Real Time for a Water Supply System

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Substantial developments in optimizing control methods for different purposes have been made in the field of fuzzy control in recent years. However, most of them are based on a known system model, whereas in practice such models are not usually available due to the complexity of the plant to be controlled. In this paper, we present a novel approach to achieve global adaptation in fuzzy controllers.The algorithm does not need a mathematical model of the plant or its approximation by means of a Jacobian matrix. Qualitative knowledge and auxiliary fuzzy controllers help the main controller to accomplish its task in real time. Application to a water supply system of Granada (Spain) is presented.

Keywords: fuzzy, control in real-time, industrial application

Tópicos:
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PAPER TRACK

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Abstract

Substantial developments in optimizing control methods for different purposes have been made in the field of fuzzy control in recent years. However, most of them are based on a known system model, whereas in practice such models are not usually available due to the complexity of the plant to be controlled. In this paper, we present a novel approach to achieve global adaptation in fuzzy controllers.The algorithm does not need a mathematical model of the plant or its approximation by means of a Jacobian matrix. Qualitative knowledge and auxiliary fuzzy controllers help the main controller to accomplish its task in real time. Application to a water supply system of Granada (Spain) is presented.

1. Introduction

As is well known, Fuzzy Logic and ANNs have proved successful in a number of applications where no analytical model of the plant to be controlled is available [1][2][3][4]. Among the different ways of implementing a neuro-fuzzy controller, adaptive and/or self-learning controllers are, at least in principle, able to deal with unpredictable or unmodelled behaviour, which enables them to outperform non-adaptive control policies when the real implementation is accomplished [5].

The development of adaptive and self-learning controllers solves one of the most important problems for the design of neuro-fuzzy controllers: the determination of the rules and the membership function parameters that define the controller. Generally, this knowledge contribution is obtained from the prior experience of a human controller. Nevertheless, there are situations in which this knowledge is not available, is incomplete or inaccurate. In this context, the development of controllers capable of generating a set of rules to obtain the desired dynamics for the plant is of great importance.

The principal aim of this article is the design of an on-line trained fuzzy system controller which can cope with the complex interactions between a non-linear plant and changeable surroundings without any off-line training process. In contrast to the various fuzzy system control schemes introduced in the bibliography, the proposed method has the following features: (a) with a modest amount of qualitative knowledge about the plant to be controlled, the approach needs no identification process, (b) the fuzzy system is trained on-line and can therefore be used with processes having time-variant characteristics and (c) the controller can start with a set of empty rules (without any information, where all the consequents are constant or randomly generated) and, by means of two auxiliary fuzzy controllers, the conclusions of the rules are learned and the output scale factor adapted.

2. Methodology for on-line adaptive and self-learning neuro-fuzzy controllers

Many of the adaptive systems referenced in the bibliography focus on modifying either the set of rules of a fuzzy system or the scale factors (in the input and output variables) [5][6].To the best of our knowledge, no papers have been published describing the accomplishment of a simultaneous adjustment of the rules and the scale factor of the output variable. The reason for this seems apparent, as argued in [7]: "output gain tuning is subsumed by look-up table modification". Indeed, by adjusting the conclusions of the rules that constitute a fuzzy system we also alter the definition range of the output; an adjustment of the output scale factor thus seems to be unnecessary and simply adds complexity to the control system. However when the control rules are unknown, and when a set of empty rules is initially used, the performance of the output scale factor plays a fundamental role in the first steps of the control process, although its significance decreases as the system evolves.

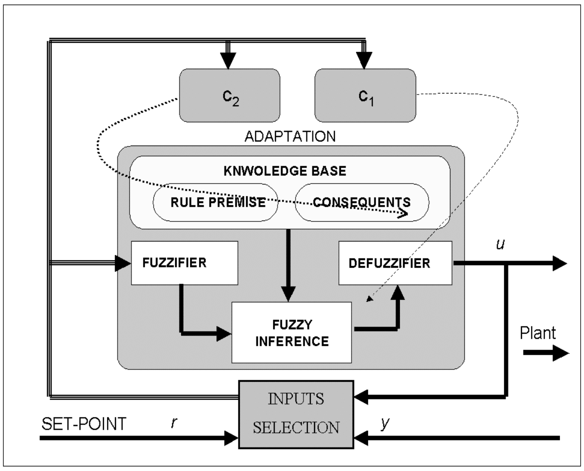

Fig. 1 Block diagram of the proposed neuro-fuzzy adaptive controller

We give below a brief summary of the algorithm proposed in [6], although the “Results” section only describes the functioning of the auxiliary controller responsible for adapting the consequents of the rules in real time (C_2 in Fig. 1). This is why Section 2.1 only includes a brief outline of the functioning of the controller C_1.

2.1 Output scale factor modification

The adaptive system is focused on modifying the output of the defuzzifier. The purpose of this is to alter the output scale in real time by using a set of neuro-fuzzy rules. A suitable adjustment of the input scale factors gives an adequate relationship between the input of the system and the neuro-fuzzy rules, while an adjustment of the output scale factor modifies the amplitude of the defuzzifier output. The output scale factor is not a constant, but rather a function dependent on the state of the system. Using the Centre of Area method, and supposing that we have n inputs, the output of the main controller is obtained according to the following equation:

$$Z^* = K_o(x_1, x_2, ..., x_n)\frac{\sum_{j=1}^{r} z_j \mu_z(z_j)}{\sum_{j=1}^{r} \mu_z(z_j)} \qquad (1)$$

where r is the number of rules and zj is the consequent (scalar) of rule j. The adaptive system that modifies the output scale factor of the main controller is also a neuro-fuzzy system (C_1 in Fig.1). This neuro-fuzzy system adjusts deficiencies in the current output of the main controller in order to correct the input to the process directly. The tuning strategy consists in setting the output scale factor as follows:

$$K_o(x_1,x_2,...,x_n) = 1 + \beta(t) \cdot F_{C1}(x_1,x_2,...,x_n) \qquad (2)$$

where $F_{C1}(\vec{x})$ is the output value of the auxiliary neuro-fuzzy controller C_1 for the input vector $\vec{x}$. As commonly occurs in the use of other paradigms intended for knowledge acquisition (mainly in the field of neural network systems), a learning factor $\beta(t)$ is employed, which decreases exponentially with time ($\beta(t) = e^{-t/\lambda}$). Therefore, modification of the output scale factor is of progressively less importance as time increases. This means that when a large number of iterations have been performed (depending on parameter λ), only the rules of the main controller will be modified. The reason for modulating the response of the auxiliary neuro-fuzzy controller C_1 by the learning factor $\beta(t)$ lies in the important effect arising from the alteration of the output scale factor, particularly in the initial iterations (when the control policy has not yet been learned).

2.2 Adaptation of the rules of the main controller in real time

A neuro-fuzzy system C_2 is used to accomplish rule learning. This system characterizes the current state of the plant through its output. Its output is referred to as F_{C2}. The sign and magnitude of this parameter provides the necessary information to modify the rules of the principal controller with the objective of altering the output of the plant. The neuro-fuzzy rules of the main controller are directly altered by this parameter, without the need for a model of the plant or the desired output at each instant of time. Nevertheless, a minimal qualitative knowledge (capable of being expressed by fuzzy terms) is required to determine the rules of the auxiliary neuro-fuzzy system together with another important parameter for the learning algorithm: *the delay of the plant*. A real plant including a term of the type and e^{-sT} in its transfer function produces a delay of T' seconds between an input vector and the corresponding response of the plant. This is a factor to take into account for modification of the rules, since otherwise the system would be adjusted wrongly. If T is the sampling time and $T' \approx mT$, after a certain time mT, not all the rules that constitute the controller are responsible for the current state of the plant. There exist some rules that contribute to a greater degree than others. To accomplish this selection, the information about the α-levels of the premises for each of the rules that constitute the main controller is used. In this paper, we propose that the modification of the rules should be proportional to the activation level such that the corrections are made in a continuous way. Thus, we define a fuzzy set FSAR (Fuzzy Set of Active Rules) that represents the degree to which the rules of the system are responsible for the current state of the plant. At time *t* the elements of this set are the rules of the system with a membership degree whose value is the magnitude of the α-level of such rules at time *t-mT*.

$$FSAR(t) = \{\alpha_i(t-T')/R_i, i = 1,\dots,r / \alpha_i(t-T') > 0\} \quad (3)$$

In order to obtain the above fuzzy set, it is necessary to store the activation degrees of every rule in each iteration, since for the following step it will be necessary to identify the rules responsible for the current state of the plant, in order to accomplish the alteration of the consequents of the rules. The length of the queue of *FSARs* will depend on the plant delay and the sample rate.

The rules of the main controller are modified on line**.** For each time *t* (except the initial iterations, where the time is less than the value of the delay of the system), the vector of the α-levels of a fuzzy inference activated in the instant *t-T'* is known. The set of rules of the main system is adapted according to the following equation:

$$\Delta R_i(t) = \begin{cases} \alpha_i(t-T')\cdot F_{C2}(\vec{x}(t)) & \text{if } R_i \in FSAR(t) \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

The index *i* runs over the whole set of rules of the system. In other words, the auxiliary system C_2 evaluates the current state of the plant and proposes a correction factor. This correction must be made only in the rules responsible for that current state, i.e. the rules activated *t-T'* seconds before, taking into account their degree of responsibility (i.e. their activation degrees).

Simultaneously, in a new matrix the integral of the absolute value of each consequent is modified and stored. This matrix is designated as Integral of Modifications (*ID*). Each one of its components is calculated as:

$$ID_i(t) = \int_{T'}^{t} |\Delta R_i(\tau)|\, d\tau \quad (5)$$

The vertical lines represent the absolute value of the interior argument. The calculus of the *ID* matrix does not start at the initial instant of control, but due to the delay of the plant, the matrix *ID* starts to be computed at the instant *mT*, and finishes when the control process ends. The index *i* runs over the number of subspaces into which the input space (number of rules) is divided. This information is of great relevance since it allows us:

1 To decide which rules are actually modified and which, on the contrary, practically maintain their initial value, since the path in the state space has not crossed the subregion of the input space that defines the premise of a specific rule or because the rule does not need to be modified.

2 With this information it is possible to simplify the number of membership functions in the input variables, selecting the most representative ones and, conversely, determine the most important ones.

Although it has been commented that the intention is to introduce a smaller quantity of *a priori* knowledge into the system, it is important to emphasize that initially the domain of each input variables must be divided into several intervals for the construction of the membership functions. With the help of *ID* it is possible to reassign the linguistic values of each of the input variables to improve the behaviour of the plant.

3. Real Application: Control of a city water supply system.

Figure 2 shows that in the case of Granada, with 300,000 inhabitants, the water intake system comprises two large reservoirs and a network of water pumped underground (for emergency situations). Water is piped to the Drinking Water Treatment Plant (DWTP) by means of canals and pipes that are several kilometers long.

The existence of distribution canals means we must consider the problem of lags in the delivery of water to the desired point. From the reservoirs to the DWTP the average time required is some two hours, and from the DWTP to the distribution deposits, some 40 minutes, depending on the volumes of water being transferred. Storage capacity is about 45,000 cubic metres, while average demand is around 90,000 cubic metres.

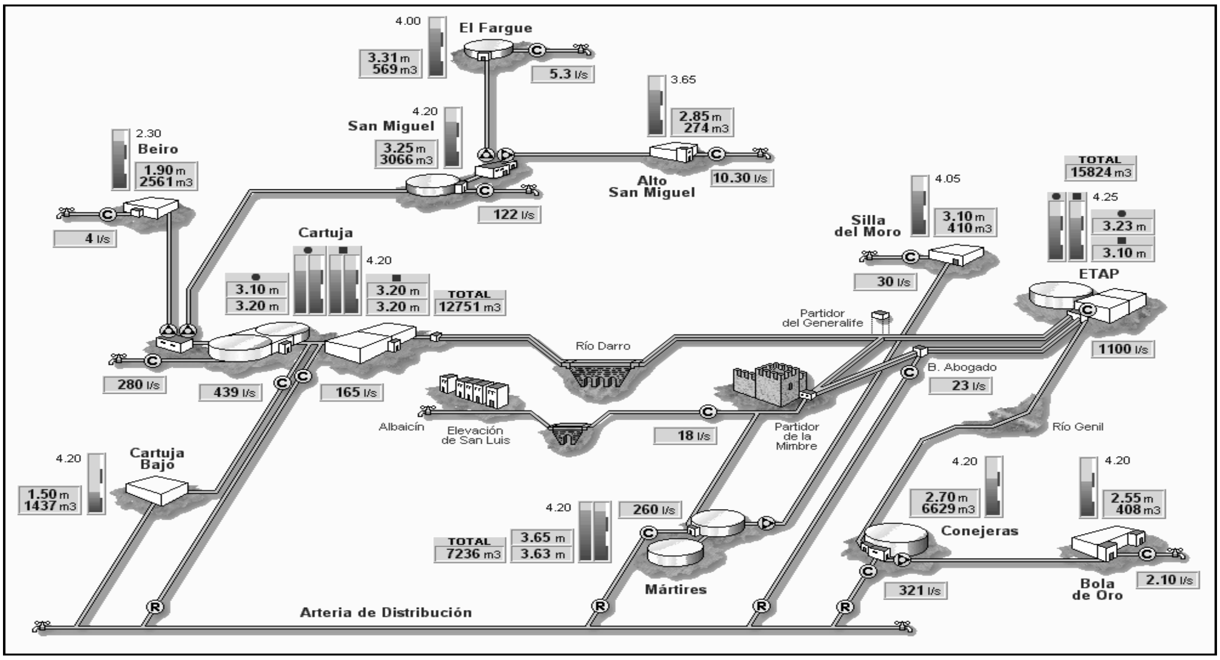

Figure 2 Water supply system of

This shortfall in storage capacity, together with the delay caused by the limitations of the supply and distribution canals, means that attention must constantly be paid to the levels of water deposits in order to anticipate fluctuations in demand and to vary the supply from the reservoirs as necessary, thus neither emptying nor overfilling the deposits.

For the above reasons, we aim to:

- Create an application to predict the following day's demand and thus be able to request the volume of water required from the reservoirs just once a day.
- Analyse daily consumption patterns so that, from the volume of stored water available and from real-time demands, the necessary corrections can be made to requests for water from the reservoirs (the personnel to carry out this task are only on duty at the reservoirs between 8 a.m and 2 p.m. on normal working days).
- Control in an autonomous fashion the main elements of the city's water supply system.

The demands made of the system by the water supply company were:

1. A decrease in the number of modifications required at the DWTP. (Fig.3)
2. All water tanks must have similar levels of deposits.

With regard to the automatic control of the system, let us first consider the city's main water supply tanks. We intend to replace the control operations carried out by expert staff with an adaptive neuro-fuzzy system.

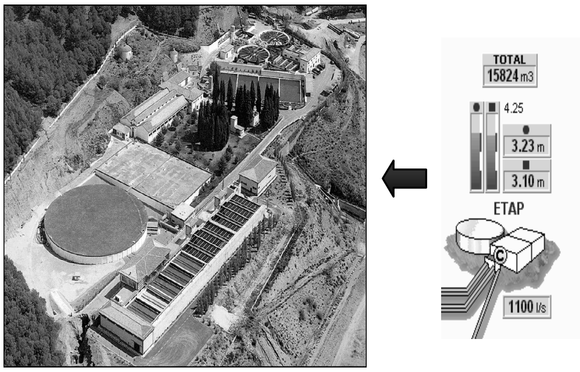

Figure 3 Drinking Water Treatement Plant (DWTP or ETAP)

Figure 4 shows that the output of water from the three main deposits varies greatly during the week (1 day=144 measurements) . This is the demands of the inhibitants of the different sector of Granada. In order to supply this output flow volume, it is necessary to modify the valve of the tanks (Figure 5). The largest output flow volume, from the DWTP, is modified two or three times per day, although in the Figure, due to sensor errors, there appear many small fluctuations which are not the consequence of control instructions from the DWTP. A primary objective is to reduce the number of daily modifications of this flow volume, as a priority of the city water company is to ensure a constant supply. Such stability would produce economic benefits, arising from the lower frequency of valve operations, as well as a stable quantity of drinking water throughout the day.

Nevertheless, the amount of water at the city's three main deposits must be maintained at suitable, and similar levels, which is the second principal objective. Clearly, these two goals are interrelated: if, for example, an excess of water is provided by the DWTP, levels at the main deposits will rise excessively and may even overflow. On the other hand, if too little water is supplied, consumption could lead to the deposits being emptied. This problem is further complicated by lags within the water distribution system.

Figure 6 shows the evolution of water levels in the three main deposits, when they are controlled by a human expert. These levels remain within a margin of security (2-4 meters) although at given times each deposit presents different levels. The second goal of the supply company was to maintain similar levels of water within each of the deposits. The reason for this is apparent. If at any time there is too much water in the network, this must be distributed equally between the three deposits so that water levels will rise equally in each and thus the excess can be incorporated without overflows. If, on the other hand, there is a shortage of water, no deposit should be allowed to empty completely, but rather the level of water within each should fall in a homogeneous fashion.

With these objectives in mind, we designed a set of neuro-fuzzy controllers for each of the main deposits and for the DWTP. In an initial, test phase the instructions given by the controllers could be used to assist the human expert in making decisions. Subsequently, after the learning phase and optimization of the system, they could work autonomously. Figure 7 shows how the neuro-fuzzy controllers react. During the first iterations, levels within the deposits do not fulfill the prerequisites. Closer examination of the first day's results (Fig. 8) reveals that each deposit presented a different pattern of variations and that the security margin was exceeded. The DWTP instructions, however, were only modified once. Despite this, after 14 days (each vertical line represents one day), the variations in the water levels in the deposits began to be satisfactory.

Finally, Fig. 9 shows the dynamics of the system over seven days, after the control rules had been adapted and learned. The pattern of water deposit levels is controlled well, and the prerequisites are fulfilled. Moreover, very few changes were made to the DWTP instructions.

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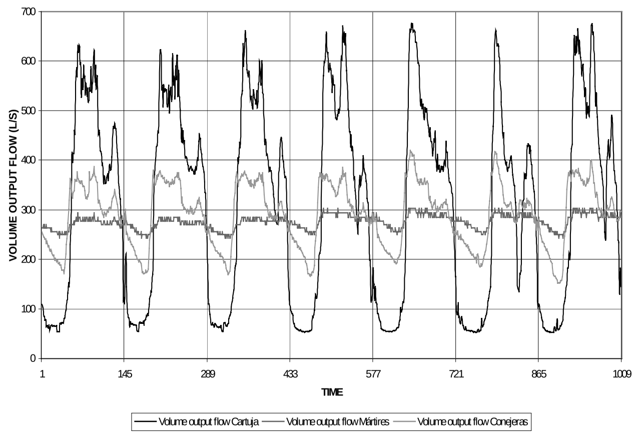

Figure 4 Output of water from the three main deposits during one week.

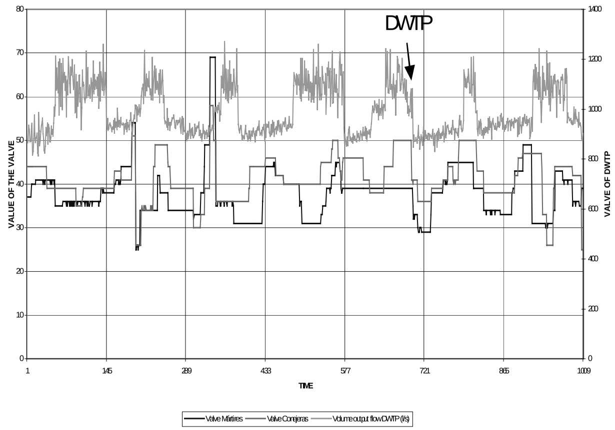

Figure 5 Modification of the main valves of the tanks and the output volume flow of the DWTP (Human expert).

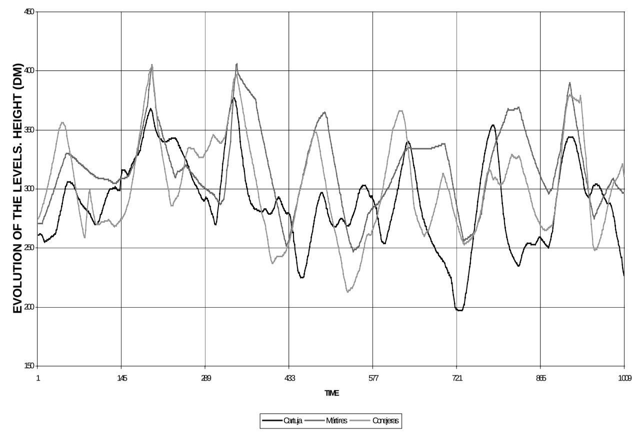

Figure 6 Evolution of water levels in the three main deposits, when they are controlled by a human expert

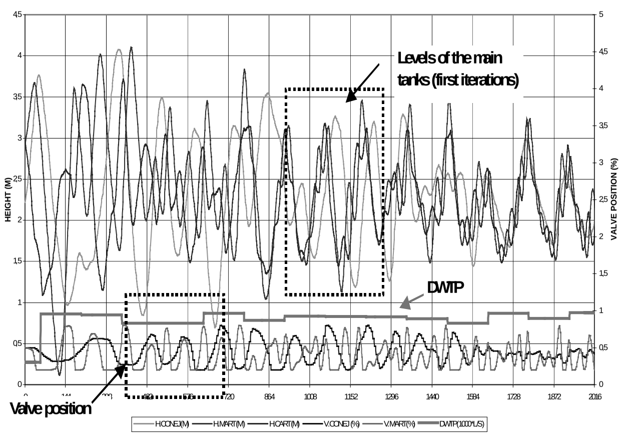

Figure 7 Behaviour of the adaptive fuzzy controller during the first iterations

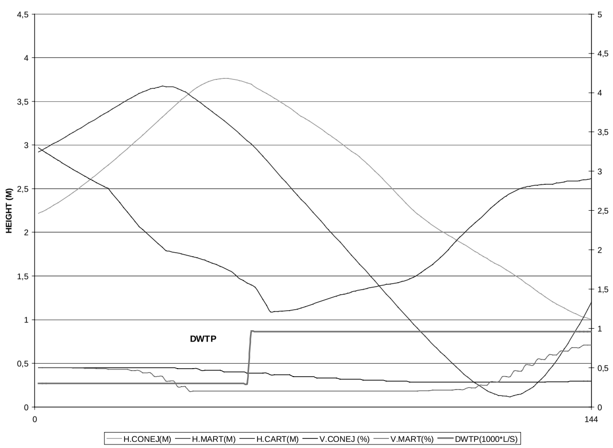

Figure 8 Closer examinations of the first day's results

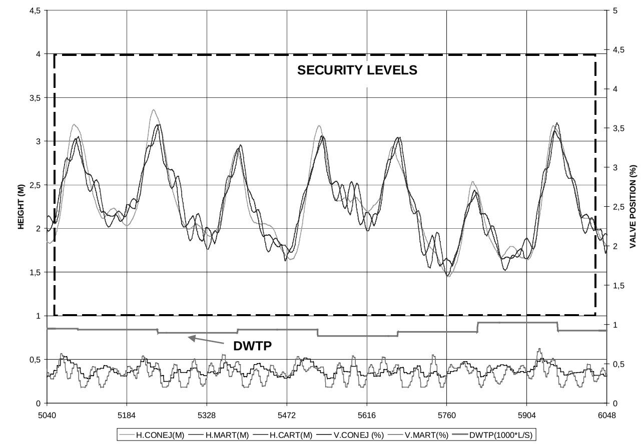

Figure 9 Dynamics of the system over seven days, after the control rules had been adapted and learned