| BULETINUL Universităţii Petrol – Gaze din Ploieşti | Vol. LXV No. 2/2013 | 49 - 56 | Seria Tehnică |
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# Wastewater pH Control Using Artificial Intelligence Techniques – A Comparative Study

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## Abstract

*The paper presents two control systems (CS) for wastewater pH control developed using artificial intelligence (AI) techniques (artificial neural networks and adaptive neuro-fuzzy systems). The goal is to achieve a comparative study of the simulation results supplied by four systems (two developed in this paper and two developed (using fuzzy logic and expert systems) in other two papers, in order to establish the artificial intelligence-based control method that is more adequate for the analyzed process, namely the wastewater pH neutralization process from a wastewater treatment plant, a process with a high nonlinear and dynamic behaviour.*

**Key words:** *artificial intelligence, neutralization process, pH control, neuro-fuzzy, neural network.*

## Introduction

In processes control, there can be used, beside conventional methods, advanced control techniques, some of these belonging to artificial intelligence (AI) domain (fuzzy logic, artificial neural networks, adaptive neuro-fuzzy systems, expert systems, genetic algorithms, etc.). The usage of one of the control methods (conventional or AI) depends on the analysed process behaviour, in this case the wastewater pH neutralisation process from a treatment plant.

In literature, there are presented systems that use AI techniques in processes control, monitoring, diagnosis and analysis such as: GESCONDA [5], ISCWAP [12], BIOEXPERT [7], EXPERT-AT [9], TELEMAC [4], EnvMAS [10], a system with fuzzy logic for the analysis of a wastewater treatment plant (WWTP) emissary level of pollution, system developed in [1], etc. According [8], the pH neutralisation process has a high nonlinear and dynamic behaviour. For the control of a process with such behaviour, AI techniques are recommended (fuzzy logic, neuro-fuzzy, neural networks, expert systems, etc.) [11].

The goal of this paper is to present and compare the simulation results (the controlled variable (pH) value, system stationary error ($e_{st}$) and transient time ($T_{tr}$)) supplied by four automatic pH control systems (two developed in this paper and the other two presented in [2] and [3]) developed using AI techniques (artificial neural networks (ANN), adaptive neuro-fuzzy systems (ANFIS), fuzzy logic and expert systems (ES)), in order to establish the AI technique that supplies the best results for the analysed problem (the wastewater pH control).

# The Wastewater pH Control Using Artificial Intelligence Techniques

## ANNpHCONTROL control system

According to [11], the artificial neural networks (ANN) can be successfully applied in the control of various treatment processes parameters (pH, level, flow, etc.), due to their learning capacity through which they may develop robust and adaptive controllers, especially in the case of complex and high nonlinear processes, such as wastewater pH neutralization process. Also, through learning, ANN can generate models for the analyzed processes directly from the data supplied by the process transducers. The architecture of the developed AS ANNpHCONTROL is presented in Figure 1.

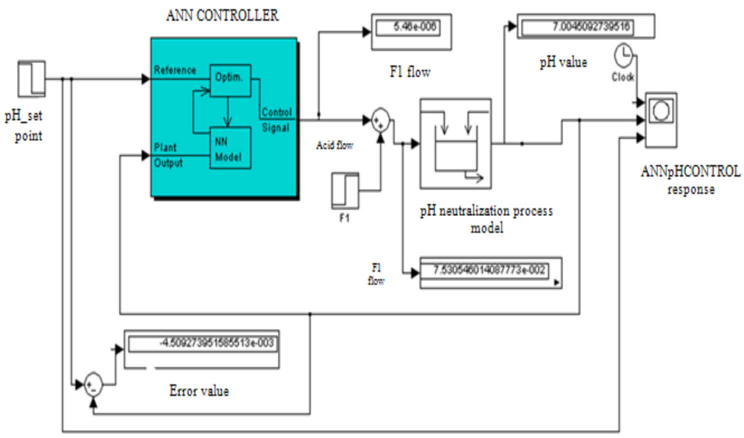


**Fig. 1.** ANNpHCONTROL architecture

For developing the ANNpHCONTROL system, it was used the Neural Network Toolbox tool from Matlab 7.9/Simulink. From the available controllers that use ANN, it was chosen the Neural Network Predictive controller (NN Predictive Controller) as a component of ANNpHCONTROL system, a controller that uses a neural model of the nonlinear process to implemented the model predictive control (MPC). The controller inputs are the reference (the pH set point) and the measurement (the pH value at the neutralisation process output), while the output is the control signal, respectively the command for acid-type neutraliser (F1) flow changing, to bring the controlled variable (pH) to its set point. The first step in MPC is that of ANN training (through the usage of the process model) to represent the process dynamics. The error between the process output ($y_p$) and the ANN output ($y_m$) is used as ANN training signal [13].

In Figure 2 there are specified the parameters that define the analysed process (minimum and maximum plant input- the acid stream flow rate F1 necessary to bring the controlled variable pH to its set point (SP), flow established according to error, minimum and maximum plant output- the controlled variable pH posible values at the process output, etc.). It is used the model of the wastewater pH neutralisation process (model presented in [6]) implemented in Simulink, model named *procesTEST* [2]. There was generated a number of one hundred training samples for ANN and there was established the number of training epochs (100) and the training function (trainlm).

For generating the training data set, there was used the *Generate Training Data* option, that opens the window presented in Figure 3, where there are presented the process input (the error value, respectively the F1 neutralizer flow) and output (the controlled variable (pH) value).

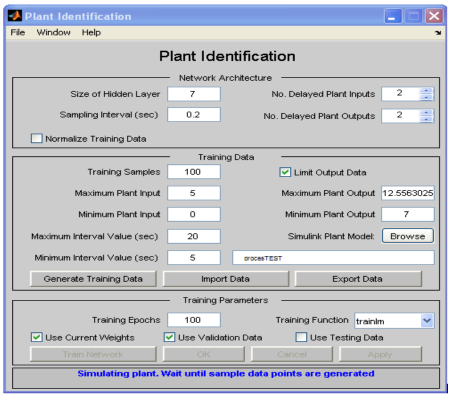


**Fig. 2.** The analysed process parameters

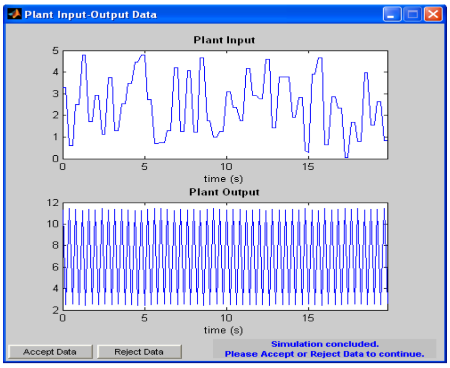


**Fig. 3.** Generating the training data

The training of the ANN was made using the generated training data set, followed by the simulation of the AS ANNpHCONTROL developed in Simulink (fig. 1), in order to obtain the simulation results. In Table 1 there are presented the simulation results supplied by developed automated ANNpHCONTROL system, system that uses an ANN controller, being highlighted the system error ($e_{st}$), the controlled variable (pH) value and the transient time ($T_{tr}$).

**Table 1.** ANNpHCONTROL simulation results

| C1 (%) | F1 (l/h) | C2 (%) | F2 (l/h) | pH SP | pH value (units) | Error ($e_{st}$) | Ttr (min.) |
|---|---|---|---|---|---|---|---|
| 0.05 | 75 | 0.05 | 70 | 7 | 7.0045 | 0.00450927 | 5 |

In Figure 4 it is presented the developed AS ANNpHController response. As it can be observed in Table 1 and Figure 4, an alkali-type pH (the controlled variable (pH)) is brought close to its set point (7) and the system error is a low one.

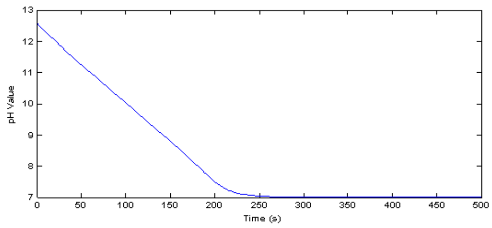


**Fig. 4.** ANNpHCONTROL response

## ANFISpHCONTROL control system

A disadvantage of fuzzy systems is the fact that the development of a consistent rule base and the permanent adaptation of it are time consuming. A solution is to add artificial neural networks (ANN) to the fuzzy systems, due to their capacity to adapt, thus being obtained the so-called neuro-fuzzy systems.

The adaptive neuro-fuzzy systems (ANFIS) are in fact adaptive neural networks that, from a functional point of view, are equivalent to Sugeno or Tsukamoto systems. In principle, an ANFIS supplies a fuzzy inference system (FIS) that, when uses the training data sets, is capable to self adjust, ability that represents a major advantage. According to [14], the ANFIS can replace almost any ANN from an CS. When a controller is developed using conventional methods, a mathematical model is necessary, while a controller developed using ANFIS needs only an ANFIS model of the system. Also, when the mathematical model of the process is not available or unknown, it can be replaced with a second trained ANFIS. The developed automatic ANFISpHCONTROL system architecture is presented in Figure 5.

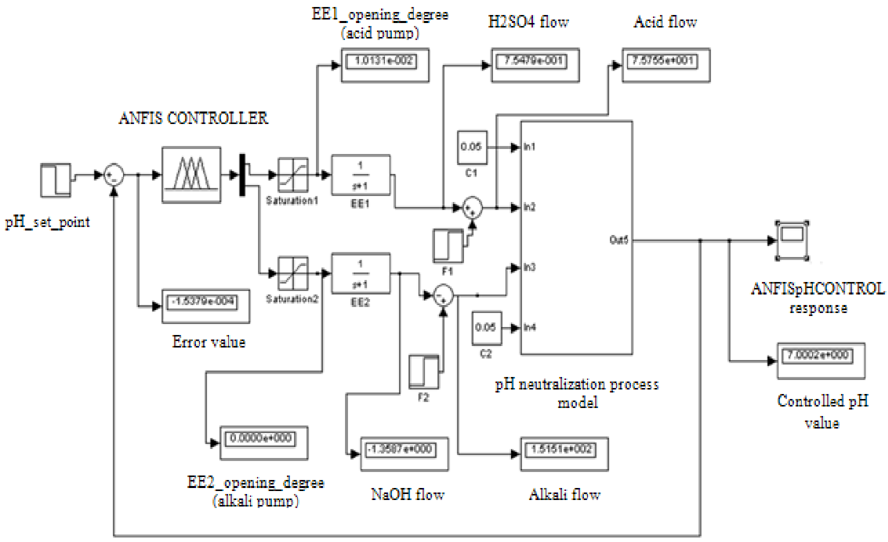


**Fig. 5.** ANFISpHCONTROL architecture

As it can be observed in Fig. 5, the ANFISpHCONTROL main elements are:

- An ANFISCONTROLLER developed in Matlab 7.9, using the Adaptive Neuro-Fuzzy Inference System (ANFIS) editor; it was considered to be a first order Sugeno fuzzy system with one input (error) and one output (command C- actuator EE1 or EE2 opening degree for acid or alkali-type neutralizer dosage flow);
- Two actuators: an acid (H2SO4) dosing pump (EE1) and an alkali (NaOH) dosing pump (EE2); depending on the error value, the controller commands the EE1 or EE2 opening degree, respectively the necessary acid or alkali- type neutraliser flow to bring the controlled variable (pH) to its set point;
- The wastewater pH neutralisation process mathematical model implemented in Simulink [2].

The controller ANFISCONTROLLER rule base has a number of nine rules, as it can be observed in Figure 6, rules automately generated using the option *Generate Fis* available from the Anfis Editor.

1. If (input1 is in1mf1) then (output is out1mf1) (1)
2. If (input1 is in1mf2) then (output is out1mf2) (1)
3. If (input1 is in1mf3) then (output is out1mf3) (1)
4. If (input1 is in1mf4) then (output is out1mf4) (1)
5. If (input1 is in1mf5) then (output is out1mf5) (1)
6. If (input1 is in1mf6) then (output is out1mf6) (1)
7. If (input1 is in1mf7) then (output is out1mf7) (1)
8. If (input1 is in1mf8) then (output is out1mf8) (1)
9. If (input1 is in1mf9) then (output is out1mf9) (1)

**Fig. 6.** ANFISCONTROLLER rule base

In Figure 6, *input1* represents the error defined as the difference between pH SP and the pH measurement at the process output, while the output is the command C, defined as the actuator EE1 or EE2 opening degree for acid or alkali-type neutralizer dosage flow. Using the option *Generate Fis* from Anfis Editor and a set of training data, there was generated a fuzzy inference system (FIS) capable to self adjust, therefore was obtained an ANFIS, named ANFISCONTROLLER. The FIS supplied by ANFIS, in principle is similar to the modified RpHfuzzy obtained within the framework of fuzzy control, but it is an improved FIS due to its capability to self adjust (ability given by the usage of FIS combined with ANN) [2].

In Figure 7 it is presented the architecture of the generated ANFIS model.

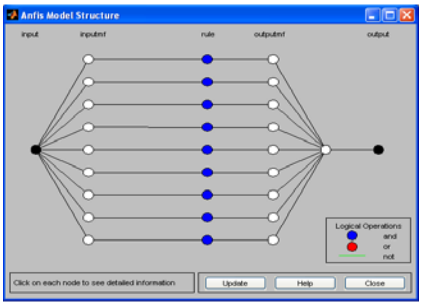


**Fig. 7.** ANFIS structure

As it can be observed in Figure 7, the model has one input (error value), one output (command C - EE1 or EE2 opening degree for acid or alkali-type neutralizer dosage flow) and a number of nine fuzzy rules. In order to train the generated FIS (Fig. 8), there was used a hybrid training algorithm that has two steps: a feed forward step and a back-propagation step.

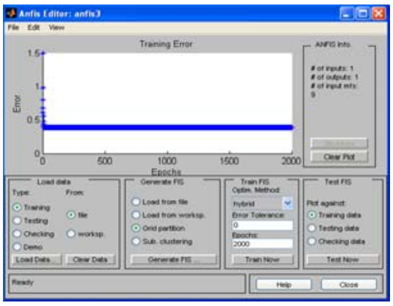


**Fig. 8.** FIS training

In Figure 9 it is presented the ANFIS model validation, using a set of validation data. As it can be observed, the generated model is a valid one due to the fact that the validation data output follows the FIS output.

**Fig. 9.** ANFIS model validation

In Figure 10 it is presented a graphical form of the relation between the ANFISCONTROLLER input (error value) and output (the command C - the EE1 or EE2 opening degree for acid or alkaly-type neutraliser dosage flow).

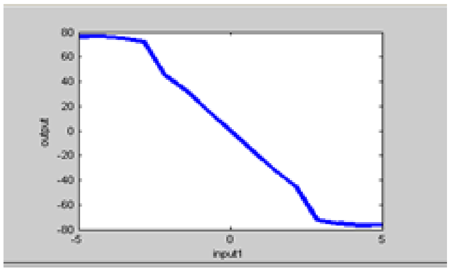


**Fig. 10.** Controller surface viewer

In Figure 11 it is presented the developed ANFISpHCONTROL system response.

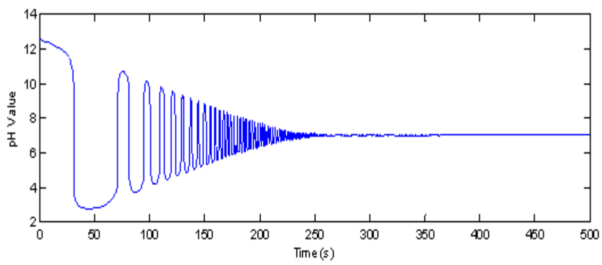


**Fig. 11.** ANFISpHCONTROL response

The simulation results of the developed CS ANFISpHCONTROL are presented in Table 2.

**Table 2.** ANFISpHCONTROL simulation results

| C1 (%) | F1 (l/h) | C2 (%) | F2 (%) | pH SP | pH value (units) | Error (est) | Ttr (min.) |
|---|---|---|---|---|---|---|---|
| 0.05 | 75 | 0.05 | 70 | 7 | 7.0002 | 0.00015379 | 6 |

As it can be observed in Table 2 and Fig. 11, when using the neuro-fuzzy control, the controlled variable (pH) was brought very close to its set point (7), with a very low error, being obtained an neuro-fuzzy controller (ANFISCONTROLLER) that, for the analyzed problem (wastewater pH control), supplies good results.

## The Comparative Study

In this section, it is presented a comparative study of the simulation results supplied by the developed systems mentioned above and the systems developed in [2, 3]. The criteria used in this study are: the system stationary error ($e_{st}$), the transient time ($T_{tr}$) and the controlled variable value (pH), values supplied by the developed systems. The goal of this study is to establish the AI technique that supplies the best results for the analysed problem, respectively for wastewater pH control. In Table 3, there are synthesized the simulation results supplied by the developed systems (ANFISpHCONTROL, ANNpHCONTROL) and the systems FUZZYpHCONTROL and ESpHCONTROL developed in [2, 3]. It must be made the following observation: the amount of time it actually takes to run a simulation depends on many factors including the complexity of the model, the solver step sizes and the computer speed.

**Table 3.** Simulation results

| The analysed parameter / Control method/ System name | pH value (units) | Stationary error $e_{st}$ | Ttr (min.) |
|---|---|---|---|
| Fuzzy/FUZZYpHCONTROL | 7.0002 | 0.00016717 | 6 |
| **Neuro-fuzzy/ANFISpHCONTROL** | **7.0002** | **0.00015379** | **6** |
| ANN/ANNpHCONTROL | 7.0045 | 0.00450927 | 5 |
| ES/ESpHCONTROL | 7.0002 | 0.00016717 | 6 |

From the simulation results presented in Table 3, it can be observed that the developed neuro-fuzzy system ANFISpHCONTROL supplies the best results, better than other AI techniques, such as fuzzy logic, ANN and ES. So, the controlled variable (pH) value is brought to 7.0002 pH units, very close to its set point (7), the stationary error ($e_{st}$) is the lowest (0.00015379), and the transient time ($T_{tr}$) is a low one (6 minutes). Beside the neuro-fuzzy control advantages, advantages given by the usage of fuzzy logic combined with ANN, another advantage is that this type of control (like fuzzy control) uses exclusively the expert knowledge regarding the analyzed process and that it can be used for non-linear processes, as the analyzed process. Therefore, the neuro-fuzzy systems (as AI technique) prove to be a useful tool, supplying good results, even in the case of a high nonlinear and complex process. For the analyzed problem, respectively for wastewater pH control, it can be concluded that all four developed systems, systems that use AI techniques (fuzzy, ANN, ANFIS and ES), supply good results, but especially the system that uses neuro-fuzzy control (ANFISpHCONTROL) due to its advantages (from which the most important is the FIS ability to self adjust) and to the applicability of this technique in the case of dynamic and high nonlinear processes.

## Conclusions

This paper analyses AI techniques (fuzzy logic, neuro-fuzzy, ANN and ES) application suitability in developing wastewater pH control systems in order to make a comparative study between the systems developed using AI techniques. So, for the analysed process (the wastewater pH neutralisation process), the control using one of the AI techniques (ANFIS) proved to supply the best results, being obtained a neuro-fuzzy controller (ANFISCONTROLLER) that can be applied for the high nonlinear and dynamic process, as for that matter, is the process of wastewater pH neutralisation. The future work consists in the development of an experimental stand for wastewater pH control, on which it will be implemented the neuro-fuzzy controller (ANFISCONTROLLER) developed in this paper.

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# Reglarea pH-ului apei uzate prin utilizarea tehnicilor de inteligenţă artificială – studiu comparativ

## Rezumat

*Lucrarea prezintă două sisteme automate (CS) pentru reglarea pH-ului apei uzate folosind tehnici ale inteligenței artificiale (rețele neuronale artificiale şi sisteme neuro-fuzzy adaptive). Scopul este acela de a realiza un studiu comparativ al rezultatelor experimentale furnizate de către patru sisteme (două dezvoltate în cadrul acestei lucrări şi două dezvoltate în cadrul altor lucrări (folosind logica fuzzy şi sistemele expert), pentru a identifica acea tehnică de reglare bazată pe tehnicile de inteligență artificială care este mai potrivită pentru procesul analizat, respectiv procesul de neutralizare a pH-ului apei uzate din cadrul unei stații de epurare , process cu un puternic comportament neliniar şi dinamic.*