Modeling, Identification and Control of Irrigation Station with Sprinkling: Takagi-Sugeno Approach

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Abstract The spray under pressure is an effective save on water. This task should be automated and controlled in order to limit the water waste and the facilities of damages. For this reason, it's necessary to find a mathematical model describing the irrigation process. In order to facilitate this step the Takagi-Sugeno fuzzy model is the best approaches of nonlinear systems representation. Various techniques are used in the literature of such systems; the clustering technique is one of the best solutions. In this paper, we'll model the irrigation station with the T-S algorithm and use the fuzzy c-means (FCM) algorithm and present the results of simulation and some validation tests and we present the stability of T-S irrigation station model.

1 Introduction

The development of a mathematical model making it possible to represent "as well as possible" the dynamic behavior of a complex real process represents a very important problem in the practical world. In recent years, and with the evolution of technology, a significant effort has been given to modeling, identification and control of such systems. The Takagi-Segeno fuzzy model (Takagi and Sugeno 1985; Grisales 2007; Li et al. 2012; Chakchouk et al. 2014) is one of the best approaches to the representation of such a process, it was widely used in many research areas, since it has an excellent ability to describe the nonlinear system.

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Indeed, the T-S fuzzy model can approximate highly nonlinear system into several locally linear subsystems interconnected. The identification problem in the T-S fuzzy model can be summarized in two steps: structure identification and parameter estimation. Several techniques were developed to conclude the modeling of these systems: we quote primarily the neuro-fuzzy technique (Daneshwar and Noh 2013; Azar 2010a) and clustering technique (Daneshwar and Noh 2013; Azar 2010a) and clustering technique (Troudi et al. 2011; Li et al. 2013; Jang et al. 2007; Pingli et al. 2006; Xu and Zhang 2009; Zahid et al. 2001; Chakchouk et al. 2014). Indeed Several researchers have noticed that a nonlinear system can be approximated by the sum of several linear sub-systems. Method of clustering proves to be an interesting technique for identification and the modelisation of the nonlinear systems. Indeed, this technique consists in approximating the total nonlinear system by a vague model of Takagi-Sugeno type. In this case, each cluster represents one fuzzy rule of Takagi-Sugeno. The number of clusters is fixed by an expert according to the type and the performances of application considered. By consequent to each cluster one correspond homogeneous zone of operation such that is defined in the form of a linear local model. We are interested to model and identify a nonlinear system by the fuzzy logic approach such as Takagi-Sugeno (T-S) approach. The latter, uses modeling containing linguistic rules to obtain the model of system outputs. Initially, we present the fuzzy logic approach design, we gives an outline on the first two models. Then, we detail (T-S) model, uses the method of fuzzy coalescence for the identification of the nonlinear systems by the fuzzy C-means (FCM) algorithm. We will in addition present tests of validation of (T-S) model. Then, we will give the results of identification and modeling of the station of irrigation by sprinkling.

The remainder of this chapter is described such as the following section. In the first section we have describe the station of irrigation by sprinkling, in which we define the practical constraints existing on the outputs pressure and flow and other components of our station, secondly, in this section we detail the operation mode and the flowcharts of the closed loop mode with any controller and how select the operation mode. In the second section we have describe the Fuzzy coalescence algorithms. Thirdly, we spend to detail the FCM algorithm step by step. Finally, we finished by application of FCM algorithm to the irrigation station by sprinkling located in the laboratory shown in the Fig. 1. After identification and modelisation with FCM algorithm it is necessary to validate our simulation results (model mathematic of our pumping station) with Root Mean Square Error test (RMSE) and the Variance accounting for test (VAF) and many other validation tests we have test the stability of our open loop model, after modelisation and identification we control our T-S obtained model by two types of controllers, PI controller of the station of irrigation and Fuzzy logic regulator, and we finish our chapter with a comparative study between these controllers.

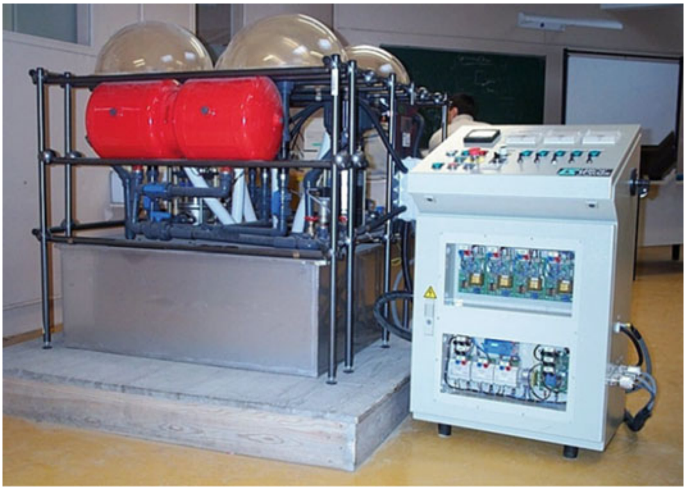


Fig. 1 Overview of the irrigation station by sprinkling

2 Description of the Irrigation Station with Sprinkling

The French company LEROY–SOMMER makes available to researchers an irrigation station (Fig. 1) with sprinkling but with practical constraints existing in the real irrigation stations (Mejri et al. 2013), this station is composed of two parts: hydraulic circuit and an electrical cabinet (Sommer 1996).

2.1 *Practical Constraints of Irrigation Station*

Before going to modeling our irrigation station, we will submit all practical constraints existing in the real irrigation stations, because the desired performances it is necessary that it respects the following constraints:

- Regulation of the flow and water pressure:

$$\begin{aligned} Q(F,t) &\Rightarrow Q_{ref} \\ P(F,t) &\Rightarrow P_{ref} \end{aligned} \tag{1}$$

- Constraints on the control:

$$N_{\min} \leq N(t) \leq N_{\max} \tag{2}$$

  The fixed speed pump will be active or not. N the numbers of turns of the variable speed pump.

- Constraints on the state:

$$Q_{\min} \leq Q(x,t) \leq Q_{\max} \tag{3}$$

x unspecified position of drain.
- Constraints on the output:

$$P_{\min} \leq P(F,t) \leq P_{\max} \tag{4}$$

- Constraints over the computing time:
Sample time: $Te = 0.2\,\text{s}$
- Energy constraints:
Concerning the operation of electrical equipment, cost optimization of pumping and turbine.
- The constraints of operation:
As they may be related to the geometry of the system levels maximum, minimum, and so on. How it should be managed to ensure the functions given to him: instructions, etc.
- The constraints of safety:
This may result in the need to keep such a volume of safety in reserve, ensuring the supply in case of unforeseen demand or incidents on the network.

2.2 Operation Mode of the Irrigation Station

The general diagram of the hydraulic system is given by the following Figs. 2 and 3:

Our station of irrigation is fed with an electrical network $400\,\text{V}(TRI + N + PE), 50\,\text{Hz}$. $(TRI + N + PE), 50\,\text{Hz}$ (Sommer 1996).

The station of irrigation starting from the cabin, we can select the operating process of the station through a selector with 6 positions

- 0 Stop;
- 1 operation in Automatic mode;
- 2 operation in Semi-automatic mode;
- 3 operation in mode Forced;
- 4 operation in mode API;
- 5 operation in mode Open loop;

Then the selection of the operating process be described in this following. (Fig. 4)

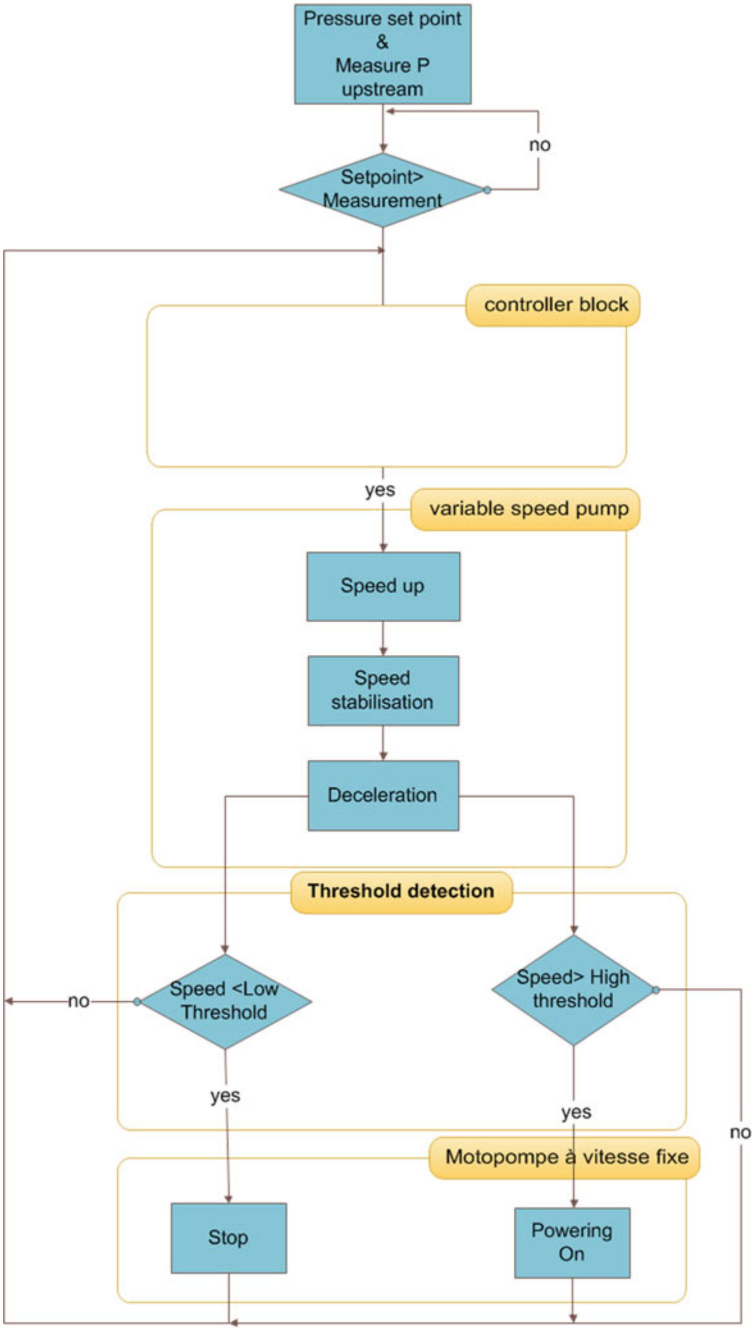


Fig. 2 Closed loop operational flowchart of the irrigation station

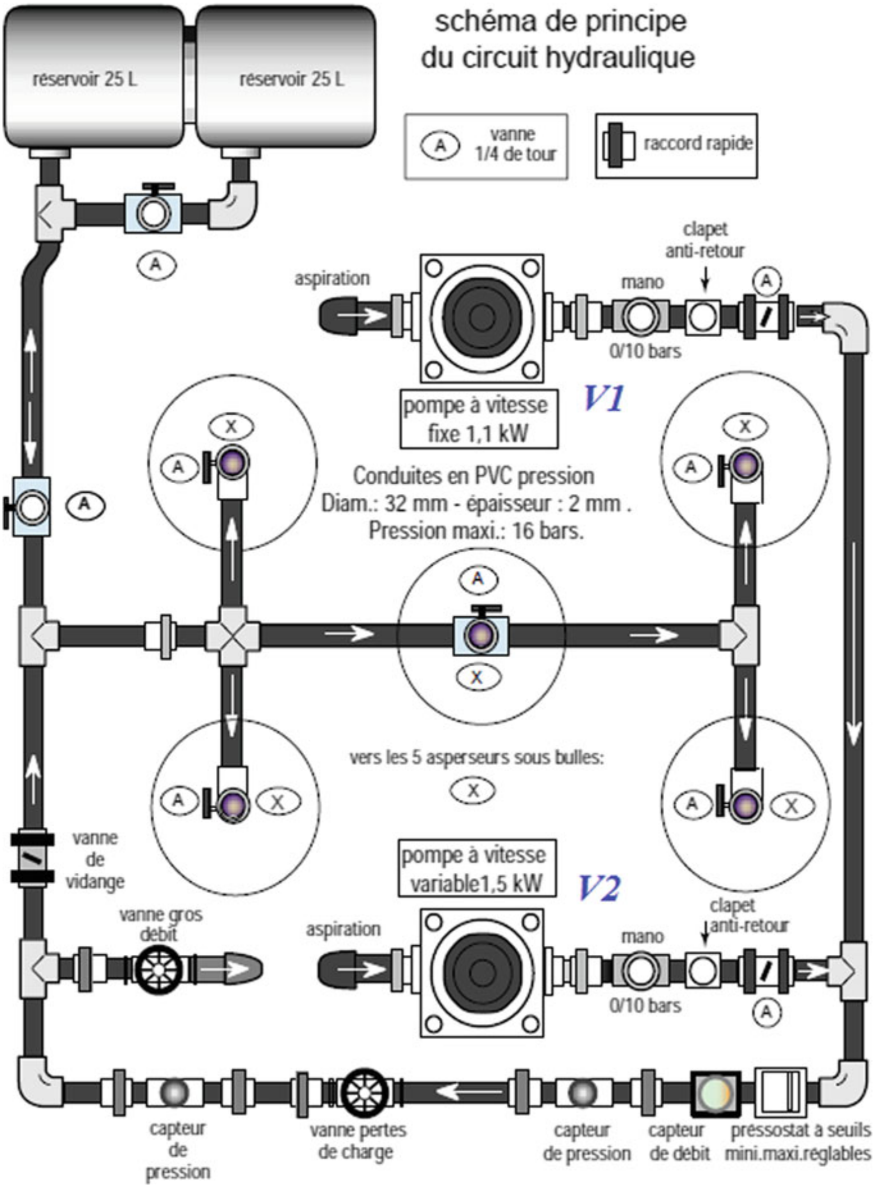


Fig. 3 General diagram of the hydraulic system

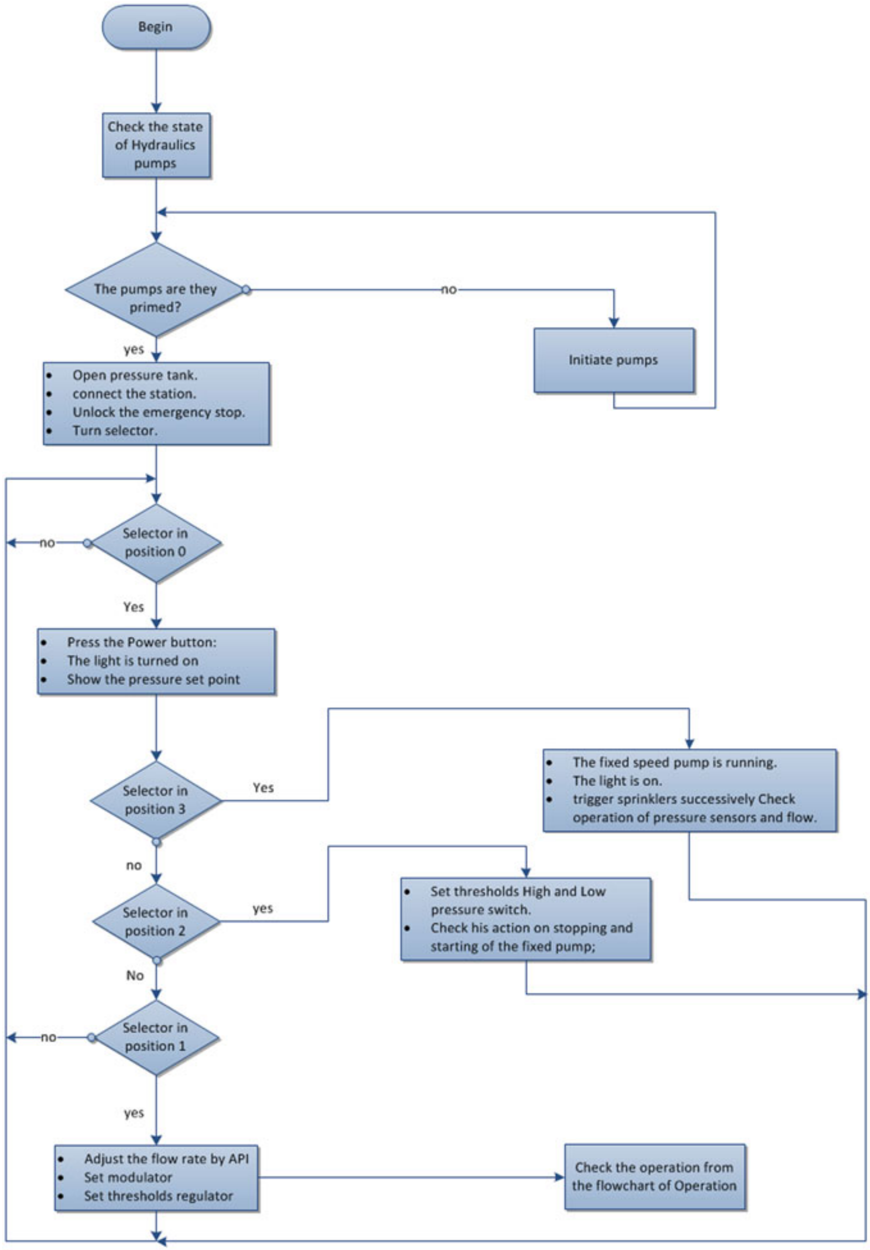


Fig. 4 Function diagram of operating modes

3 Identification and Modeling of the Irrigation Station

The implementation of a mathematical model of a complex real process operating in a stochastic environment draw the attention of many researchers in various disciplines of science and technology. In this context the use of traditional methods of modeling and identification in order to estimate the parameters of such a type of process cannot satisfy the desired performance indices (speed, accuracy and stability). To overcome this problem, other techniques such as fuzzy logic (Azar 2010b, 2012) and more particularly the T-S fuzzy model showed a good result in the identification of these processes types.

3.1 Fuzzy Coalescence Algorithms for System Identification

Let us consider a system described by the following differential equation:

$$y(k) = f_{NL}(x_k) \tag{5}$$

with x_k represent the observation vector, $x_k \in R^n$. The most used algorithms of fuzzy coalescence for the identification parameters of 5 are as follows:

- The algorithm of the fuzzy C-averages, or fuzzy c-Means (FCM) (Bezdek 1981; Chen et al. 1998),
- The algorithm of Gustafson-Kessel (GK) (Gustafson and Kessel 1979),
- The NRFCM algorithm (Soltani et al. 2012).

All these algorithms are based on their minimization of a function objectifies form (Troudi et al. 2012):

$$J(X, U, V) = \sum_{k=1}^{N} \sum_{i=1}^{c} (\mu_{ik})^m (x_k - v_i)^T M (x_k - v_i) \tag{6}$$

where: $X = \{x_k/k = 1, 2, \ldots, N\}$, such that N donate the number of observations; $U = [\mu_{ik} \in [0, 1]^{(c \times N)}]$, the fuzzy partition matrix of data vector X: with

$$\sum_{i=1}^{c} \mu_{ik} = 1 \quad 1 \leq i \leq c \tag{7}$$

V: The prototype clusters vector,

$V = \{v_1, v_2, \ldots, v_c\}$, where c represents the rule number (or of clusters) and $v_i \in R^n$,

m: represent the weighting degree

This parameter influences directly on the form of cluster in data space. Indeed, when m is close to 1, the function of the membership of each cluster becomes almost Boolean i.e., $\mu_{ik} \in \{0, 1\}$. Whereas when m becomes very large, the partition becomes fuzzier and $\mu_{ik} = 1/c$

Generally m is selected between 1.5 and 2.5 but in several applications, it is selected between 2 and 4.

In the following section, we present the fuzzy c-means algorithm.

3.2 Fuzzy c-Means (FCM) Algorithm

This method is based on minimization of the criterion obtained by the addition of the standardization constraint (Troudi et al. 2011).

$$J(X, U, V) = \sum_{k=1}^{N} \sum_{i=1}^{c} (\mu_{ik})^m (x_k - v_i)^T M (x_k - v_i) + \sum_{k=1}^{N} \lambda_k \left[\sum_{i=1}^{c} \mu_{ik} - 1 \right] \quad (8)$$

In this case the minimization of the criterion 8 can be solved by cancelling the derivative of J where the variables are U, V and λ. The solution of this criterion is given by:

$$\begin{aligned} v_i &= \frac{\sum_{k=1}^{N} (\mu_{ik})^m \cdot x_k}{\sum_{k=1}^{N} (\mu_{ik})^m} \\ \mu_{ik} &= \frac{1}{\sum_{j=1}^{c} \left(d_{ik}/d_{jk} \right)^{\frac{2}{m-1}}} \end{aligned} \quad (9)$$

where d_ik: represent the distance enters X_k and v_i

$$d_{ik} = (x_k - v_i)^T M (x_k - v_i) \quad (10)$$

M: generally selected equal to the identity. The prototype vector of the clusters is given by:

$$d_{ik}^2 = (x_k - v_i)^T (x_k - v_i) \quad i = 1, \ldots, c;\ k = 1, \ldots., N \quad (11)$$

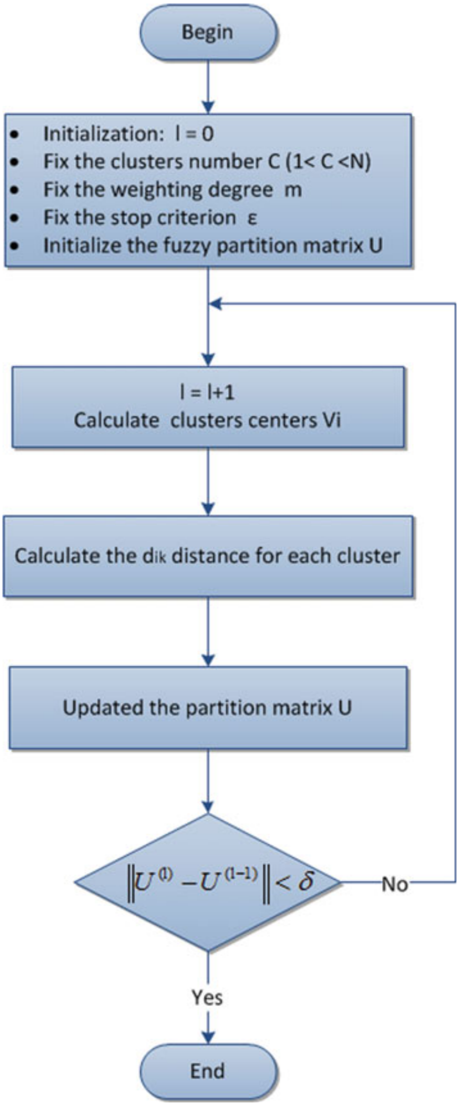
The iteration count of c-means algorithm is selected according to the precise details required by the expert and according to the type of application considered. The criterion of the stop is selected by satisfying the following condition:

$$\left\| U^{(l)} - U^{(l-1)} \right\| < \delta \quad (12)$$

where l is the iteration count.

Fuzzy c-means algorithm (FCM): Being given a whole of data X, FCM algorithm is described by the following stages (Fig. 5):

Fig. 5 Fuzzy c-means algorithm (FCM)



The FCM Algorithm converges in general towards a local minimum of the objective function. Its performance depends on several factors such as:

- The cluster number;
- Choice m;
- Choice of stop criterion.

3.3 Determination of Consequent System Parameters

The identification of consequent parameters is necessary to determine the equivalent TS model such system, we find in the literature many identification methods such as the method of ordinary least square (Bertrand and Moonen 2012) (LMS used for linear system) Method of recursive least square (RLS) (Duan et al. 2011), weighted least square (WLS) (Li et al. 2009), recursive least square weighted (RWLS) (Soltani and Chaari 2013) (this method is used for the noisy nonlinear systems).

In our case we used in the identification algorithm method of recursive least square (RLS) (Duan et al. 2011; Chakchouk et al. 2014).

We know the form of T-S model $f_i = a_i^T x + d_i$, then the vector of consequent parameters written as follow:

$$\theta_i = \left[a_i^T, d_i\right]^T \tag{13}$$

the increased regression matrix is defined by:

$$X_e = [X, 1] \tag{14}$$

then we defined the gains matrix with the follow equation:

$$P(N) = \left[X^T(N) \cdot X(N)\right]^{-1} \tag{15}$$

$P(N)$ can be written as follows:

$$P^{-1}(N) = \lambda(N) + \lambda(N) \cdot \mu(N) \cdot x\big(N) \cdot x^T(N)\big) \tag{16}$$

If we applied the matrix inverse theorem then:

$$P(N) = \frac{1}{\lambda}\left[P(N-1) - \frac{P(N-1) \cdot x^T(N) \cdot x(N) \cdot P(N-1)}{\frac{1}{\mu(N)} + x^T(N) \cdot P(N-1) \cdot x(N)}\right] \tag{17}$$

Then we defined the gain $G(N)$ with the following equation:

$$G(N) = \left[\frac{P(N-1) \cdot x^T(N)}{\frac{1}{\mu(N)} + x^T(N) \cdot P(N-1) \cdot x(N)}\right] \tag{18}$$

Then the regression matrix and the parameters consistent vector is as follow:

$$\begin{aligned}\theta(N) = {} & \left[I - G(N)x^T(N)\right]\theta(N-1) \\ & + \mu(N)\left[P(N-1)x(N) - G(N)x^T(N)P(N-1)x(N)\right]y(N)\end{aligned} \tag{19}$$

If we factorize the Eq. 15, we have:

$$\theta(N) = \theta(N-1) + G(N)\left[y(N) - x^T(N)\theta(N-1)\right]y(N) \tag{20}$$

3.4 Application of FCM Algorithm on the Station of Irrigation by Sprinkling

Let us consider a system described by the Eq. 6. Firstly, we approximate the nonlinear function Eq. 6 by the model of Takagi-Sugeno (TS):

$$R^i : if\ x_{k1}\ is A_{i1}\ and\ x_{k2}\ is A_{i2}\ and \ldots and\ x_{kn}\ is A_{in}\ then\ y^i = a_i^T x_k + b_i \tag{21}$$

To represent the rule, we need use observations vector $x_k = [x_{k1}, x_{k2}, \ldots, x_{kn}]^T$ the units fuzzy $A_{i1}, A_{i2}, \ldots, A_{in}$ to identify the parameters in the model 21, we builds the matrix of regression X and the vector of the output Y starting from measurements resulting from the system such as: $X = \left[x_1^T, x_2^T, \ldots, x_N^T\right]^T$ *and* $Y = [y_1, y_2, \ldots, y_N]^T$ with $N \gg n$.

The identification of T-S model parameters requires a taking away of the real signals of irrigation station. Using a numerical oscilloscope, we took the real dynamics of pressure and flow of the station of irrigation by sprinkling, then (Figs. 6, 7 and 8):

These results are taken from connectors of the cabinet.

In order to initialize the iteration count l = 0, we fix the weighting degree m = 2.75 what makes it possible to initialize the partial random matrix U. We pass

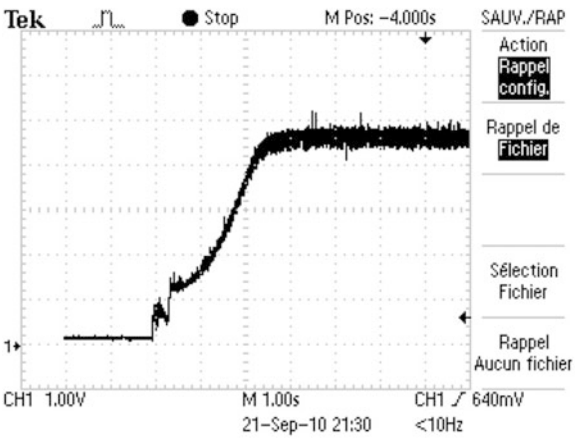


Fig. 6 Real curve of the pressure evolution

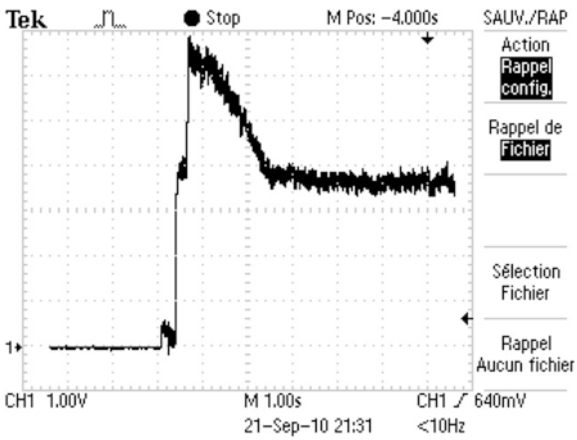


Fig. 7 Real curve of the flow evolution

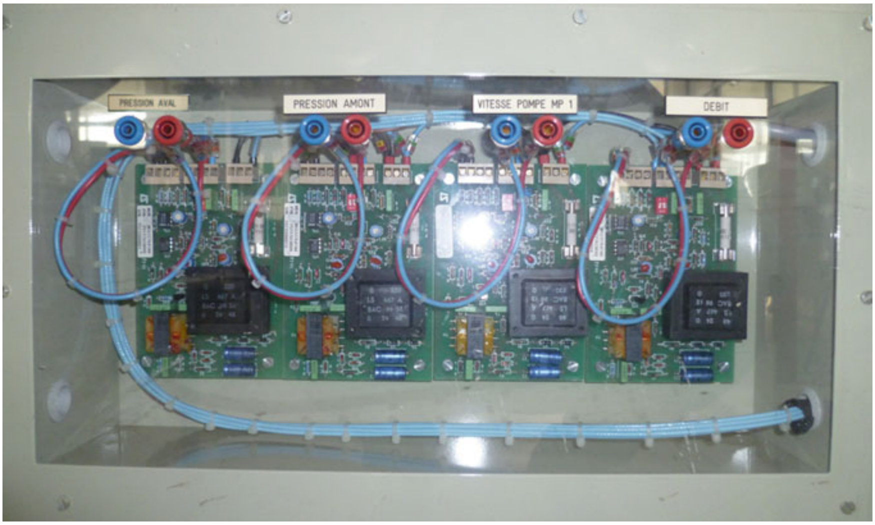


Fig. 8 Connectors of sampling signals (pressure and flow)

then to the choice of the number of clusters. We apply the classification entropy test CE for each outputs pressure (P) and flow (Q). We noted *CEP CEQ* respectively.

$$\begin{aligned} C_{ec}(c) &= \frac{1}{N}\sum_{k=1}^{N}\sum_{i=1}^{c}\mu_{ik}\log(\mu_{ik}) \\ C_{opt} &= \min[C_{ec}(c)] \end{aligned} \tag{22}$$

Then the optimal number of clusters is equal to 3 as it indicates in the 1 (Figs. 9, 10 and Table 1).

The excitation signal must be rich to run the system in all operating region. In order to reach all steps, the simulation results of the FCM algorithm are given by the following Figs. 11 and 12.

Algorithm FCM is followed the real data input of pressure and flow. It is noticed that the error between the evolution of the real and estimated pressure is almost null even for flow. The station of irrigation by sprinkling made up of two nonlinear systems in the same way input and different output, one of pressure and the other of flow, each one partitioned in 3 subsystems. We obtain the following results:

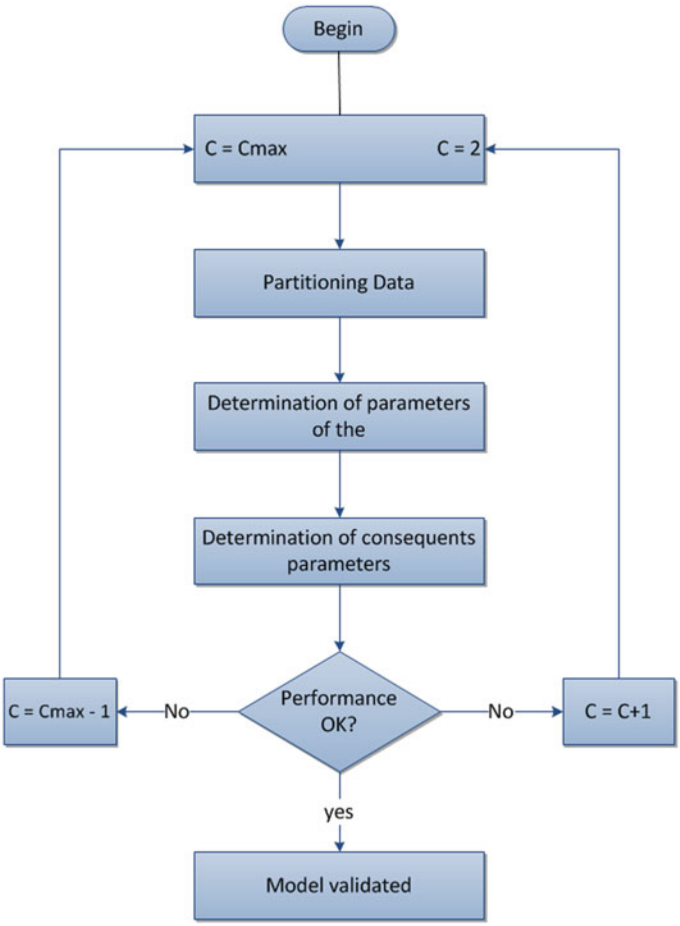


Fig. 9 Diagram of cluster number choice

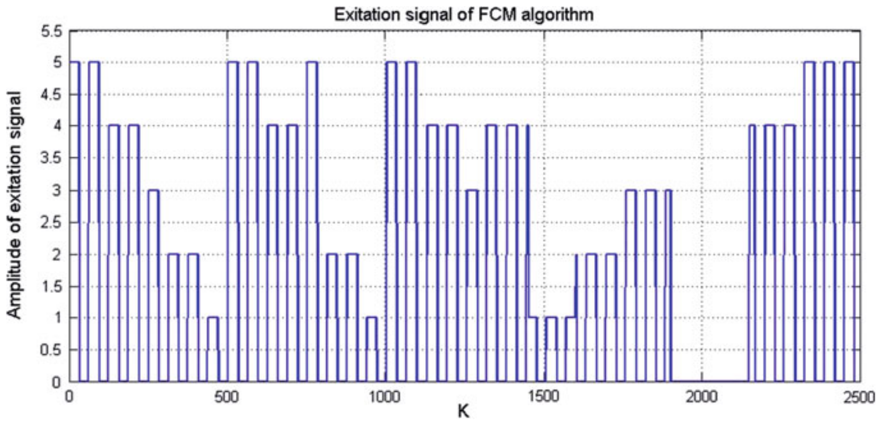


Fig. 10 Excitation signal of FCM algorithm

Table 1 Results of classification entropy test

	C = 2	C = 3	C = 4	C = 5
CEP (10^{-6})	−0.491	−5.21	−0.41	−1.18
CEQ (10^{-6})	−5.4	−10.8	−3.35	−3.58

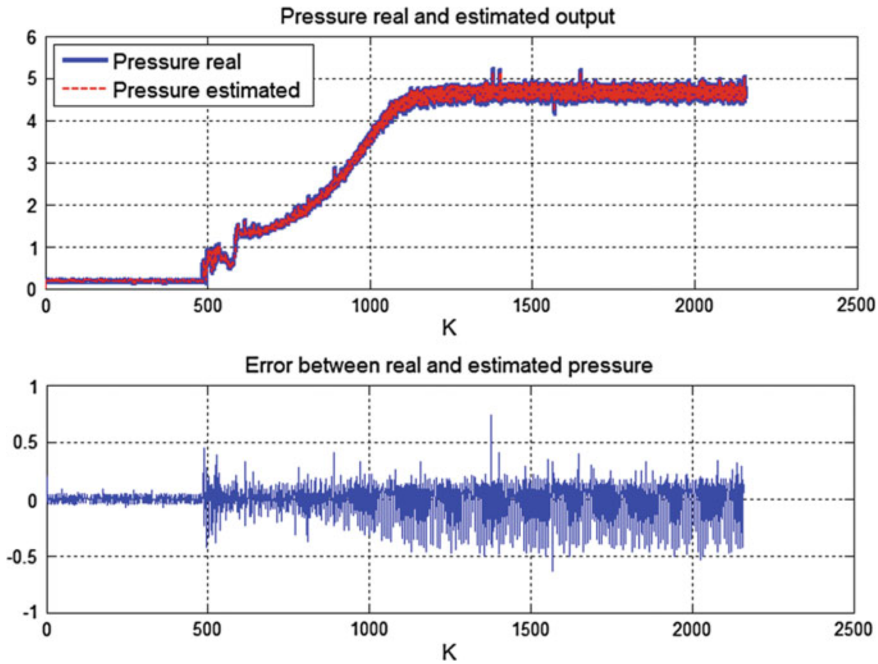


Fig. 11 Simulation results of FCM algorithm for the pressure output

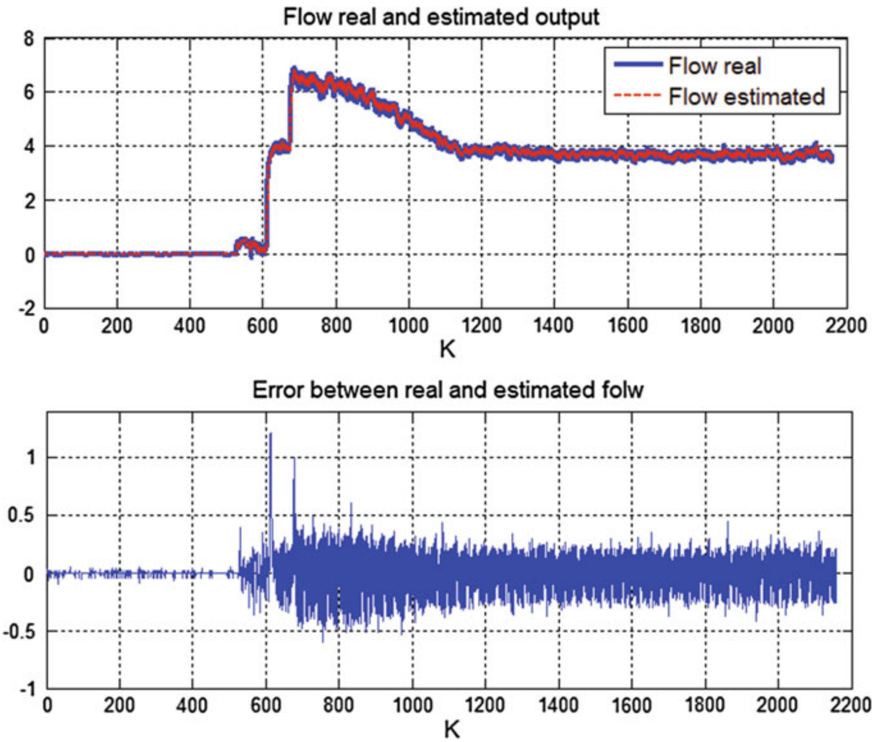


Fig. 12 Simulation results of FCM algorithm for the flow output

- For the pressure sub-systems:

$$\begin{cases} R_{p1} : y_{P1}(k) = 1.0853y_p(k-1) - 0.1744y_p(k-2) + 0.0570u(k-1) + 0.0318u(k-2) \\ R_{p2} : y_{P2}(k) = 1.0851y_p(k-1) - 0.1743y_p(k-2) + 0.0565u(k-1) + 0.0320u(k-2) \\ R_{p2} : y_{P2}(k) = 1.0852y_p(k-1) - 0.1750y_p(k-2) + 0.0560u(k-1) + 0.0315u(k-2) \end{cases}$$

- For the flow sub-systems:

$$\begin{cases} R_{Q1} : y_{Q1}(k) = 1.0853y_Q(k-1) - 0.1744y_Q(k-2) + 1.4118u(k-1) - 1.31u(k-2) \\ R_{Q1} : y_{Q1}(k) = 1.0851y_Q(k-1) - 0.1743y_Q(k-2) + 1.4116u(k-1) - 1.33u(k-2) \\ R_{Q1} : y_{Q1}(k) = 1.0852y_Q(k-1) - 0.1750y_Q(k-2) + 1.4120u(k-1) - 1.31u(k-2) \end{cases}$$

For the total identification of system we can draw a rule for each subsystem (flow and pressure) as being modeling and linearization of the whole system, through intermediary of the Eq. 23:

$$y(k+1) = \frac{\sum_{i=1}^{c} \mu_{ik} \cdot (x(k)) \cdot y_i(k+1)}{\sum_{i=1}^{c} \mu_{ik} \cdot (x(k))} \tag{23}$$

Then the global rule of the pressure output is as follow:

$$\begin{aligned} R_{PG} : y_{PG}(k) =& 1.0851 y_p(k-1) - 0.1745 y_p(k-2) \\ &+ 0.0563 u(k-1) + 0.0317 u(k-2) \end{aligned} \tag{24}$$

and the global rule of flow output is as follow:

$$\begin{aligned} R_{QG} : y_{QG}(k) =& 1.0851 y_Q(k-1) - 0.1745 y_Q(k-2) \\ &+ 1.4116 u(k-1) - 1.32 u(k-2) \end{aligned} \tag{25}$$

thus, the open loop transfer functions are:

$$\begin{cases} H_{BOP} = \dfrac{0.05632z + 0.0317}{z^2 - 1.0851z + 0.1745} \\ H_{BOQ} = \dfrac{1.4116z - 1.32}{z^2 - 1.0851z + 0.1745} \end{cases} \tag{26}$$

The discrete state representation associated with system 26:

$$\begin{cases} \begin{bmatrix} P_{k+1} \\ Q_{k+1} \end{bmatrix} = \begin{bmatrix} 0.1422 & -0.4403 \\ 0.0917 & 0.9428 \end{bmatrix} \begin{bmatrix} P_k \\ Q_k \end{bmatrix} + \begin{bmatrix} 0.0917 \\ 0.0119 \end{bmatrix} u_k \\ y_k = \begin{bmatrix} 0 & 4.7235 \\ 14.7535 & 4.9165 \end{bmatrix} \begin{bmatrix} P_k \\ Q_k \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \end{bmatrix} u_k \end{cases} \tag{27}$$

We introduce the delay $\tau = 5\,\text{s}$ into the model obtained, The system sampling period is chosen $T_e = 0.2$ s then the delay $\tau = 5\,\text{s}$ is calculated at field discrete time by $z^{-\frac{\tau}{T_e}} = z^{-\frac{5}{0.2}} = z^{-25}$. The system 26 becomes:

$$\begin{cases} H_{BOP} = z^{-25} \dfrac{0.05632z + 0.0317}{z^2 - 1.0851z + 0.1745} \\ H_{BOQ} = z^{-25} \dfrac{1.4116z - 1.32}{z^2 - 1.0851z + 0.1745} \end{cases} \tag{28}$$

3.5 Validation Tests of T-S Model

Therefore, to ensure that the model obtained from the estimation it is compatible with other forms of inputs to represent correctly system functioning to identify. In this paragraph, statistical tests to validate a fuzzy model based on Root Mean Square Error test, Variance accounting for, the residues autocorrelation function and on the cross-correlation between residues and other inputs in the system.

- Root Mean Square Error test (RMSE) (Troudi et al. 2011):
  This is an overall measure of the deviation of total points number from the expected value.

$$RMSE = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(y_k - \hat{y}_k)^2} \tag{29}$$

- Variance accounting for test (VAF) (Troudi et al. 2011):
  This criterion evaluates the quality percentage of a model by measuring the normalized variance of the difference between two signals.

$$VAF = 100\,\%\left[1 - \frac{var(y - \hat{y})}{var(y)}\right] \tag{30}$$

- Autocorrelation function of the residues:

$$\hat{r}_{\varepsilon\varepsilon}(\tau) = \frac{\sum_{k=1}^{N-\tau}\left(\varepsilon(k,\hat{\theta}) - \bar{\varepsilon}\right)\left(\varepsilon(k-\tau,\hat{\theta}) - \bar{\varepsilon}\right)}{\sum_{k=1}^{N}\left(\varepsilon(k,\hat{\theta}) - \bar{\varepsilon}\right)^2} \tag{31}$$

- Cross-correlation between residues and inputs previous:

$$\hat{r}_{u\varepsilon}(\tau) = \frac{\sum_{k=1}^{N-\tau}(u(k) - \bar{u})\left(\varepsilon(k-\tau,\hat{\theta}) - \bar{\varepsilon}\right)}{\sqrt{\sum_{k=1}^{N}(u(k) - \bar{u})^2}\sqrt{\sum_{k=1}^{N}\left(\varepsilon(k,\hat{\theta}) - \bar{\varepsilon}\right)^2}} \tag{32}$$

  with

$$\begin{aligned}\bar{\varepsilon} &= \frac{1}{N}\sum_{k=1}^{N}\varepsilon(k)\\ \bar{u} &= \frac{1}{N}\sum_{k=1}^{N}u(k)\end{aligned} \tag{33}$$

  ε: Is the prediction error and $u(k)$ is the system input. $x(k)$ can take either the value ε or $u(k)$. Ideally, if the model is valid, the result of these correlation tests gave the following results:

$$\hat{r} = \begin{cases} 1, & \tau = 0 \\ 0, & \tau \neq 0 \end{cases} \text{et} \hat{r}_{u\varepsilon}(\tau) = 0, \quad \forall\ \tau \tag{34}$$

Typically, we verified that the functions $\hat{r}$ are zero for the interval $\tau \in [-20, 20]$ with a confidence interval of 95 %, then:

$$\frac{-1.96}{\sqrt{N}} < \hat{r} < \frac{1.96}{\sqrt{N}}. \tag{35}$$

3.6 Results of Validation Tests

- Root Mean Square Error test (RMSE):

$$\begin{cases} RMSE_{pressure} = 0.1471 \\ RMSE_{flow} = 0.1926 \end{cases} \tag{36}$$

- Variance accounting for test (VAF):

$$\begin{cases} VAF_{pressure} = 99.6090\ \% \\ VAF_{flow} = 99.3272\ \% \end{cases} \tag{37}$$

- Autocorrelation and cross-correlation function results (Figs. 13 and 14):

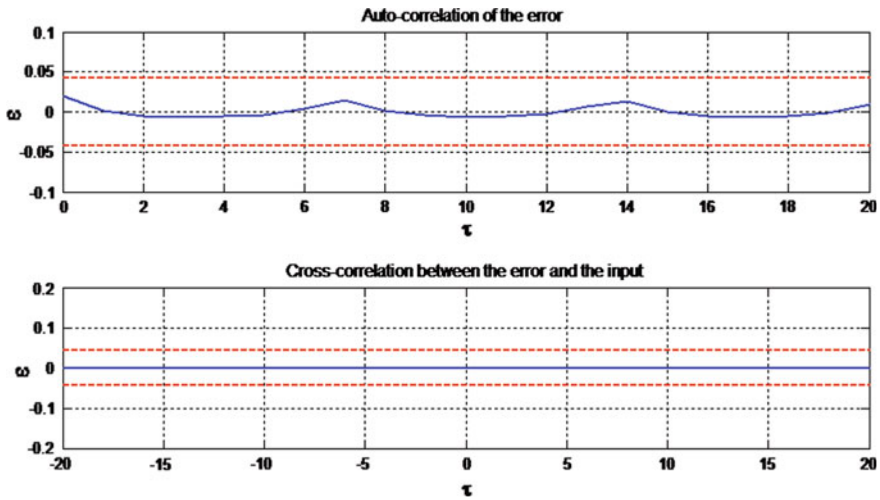


Fig. 13 Validation results autocorrelation and cross-correlation of pressure output

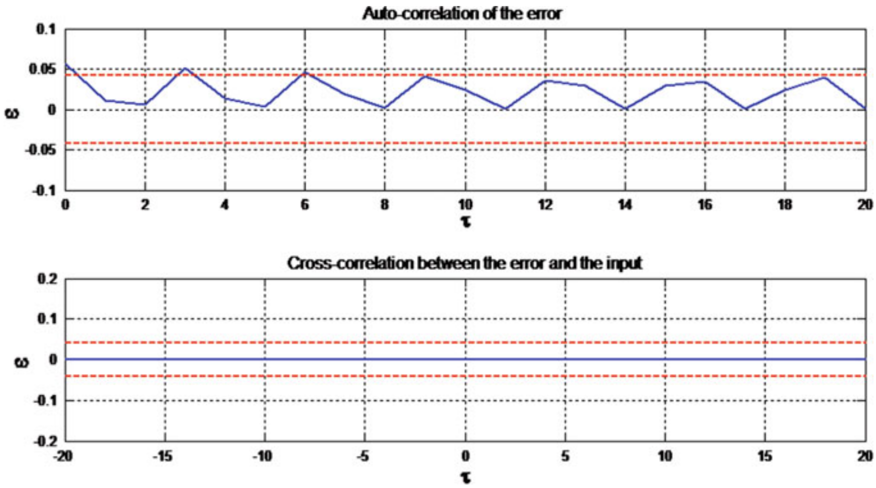
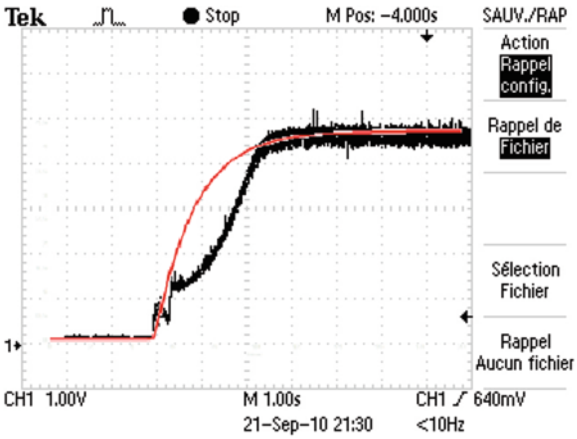


Fig. 14 Validation results autocorrelation and cross-correlation of flow output

Fig. 15 Comparison between measured and estimated pressure



A comparison was made between the estimated outputs and actual outputs collected using a digital oscilloscope (Figs. 15 and 16).

The results simulations of irrigation station model are confused with those of the real taking away.

3.7 Stability Analysis

In this part we interested to study the stability of estimated model, first of all will analyze the behavior of the discrete model obtained.

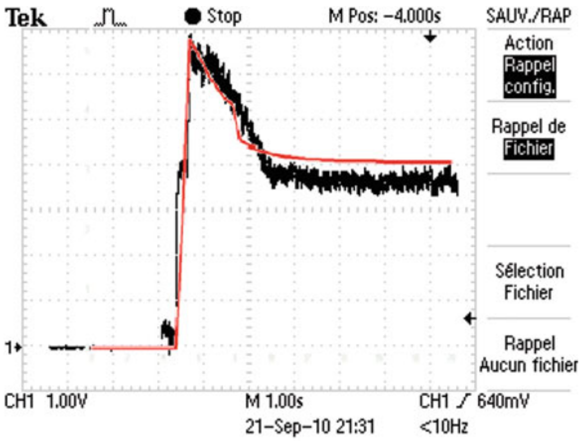


Fig. 16 Comparison between measured and estimated flow

- Lemma 1:
  A linear dynamic system is stable if and only if, isolated from its equilibrium position by an external request, the system returns to this position when the request ceased (Eivd 2005).
- Lemma 2:
  A discrete linear dynamic system is stable, if and only if, all poles of transfer function are located inside the unit disc.

$$|p_i| < 1 \tag{38}$$

Initially, we referring to lemma 1 we will test the stability of irrigation station model by impulse response which gives Fig. 17:

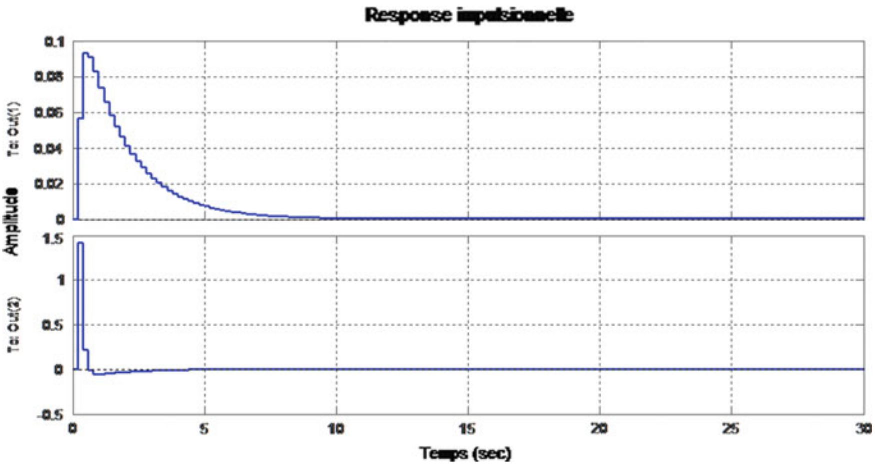


Fig. 17 Impulse response of the system

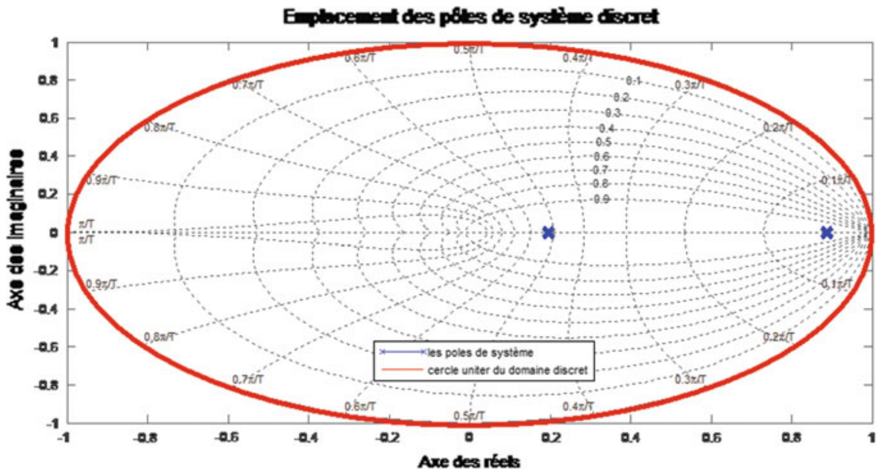


Fig. 18 Location of discrete time system poles

The test of stability by placement of the poles in the discrete place of the poles, gives Fig. 18:

We noticed well that the model obtained is a model associated with a stable system from where the poles modules are strictly lower than one.

4 Control of Irrigation Station with Sprinkling

4.1 Control of Station with PI Regulation

The irrigation station is equipped with a PI controller card which is provided by LEROY-SOMMER, this controller ensures specific control for the pumps. The originators in the LEROY-SOMMER company (Sommer 1996), chooses the parameters of following adjustments $K_p = 0.5 \quad T_i = 1$ m.

$$\frac{\mathrm{U(s)}}{\varepsilon(s)} = K_p\left(1 + \frac{1}{T_i s}\right) \tag{39}$$

The form of discrete regulator PI is given by (Chakchouk et al. 2014) (Fig. 19):

$$\frac{\mathrm{U(s)}}{\varepsilon(s)} = \frac{K_p\left(1 + \frac{T}{T_i}\right) - K_p z^{-1}}{1 - z^{-1}} = \frac{r_0 + r_1 z^{-1}}{1 - z^{-1}} = \frac{r_0 z + r_1}{z - 1} \tag{40}$$

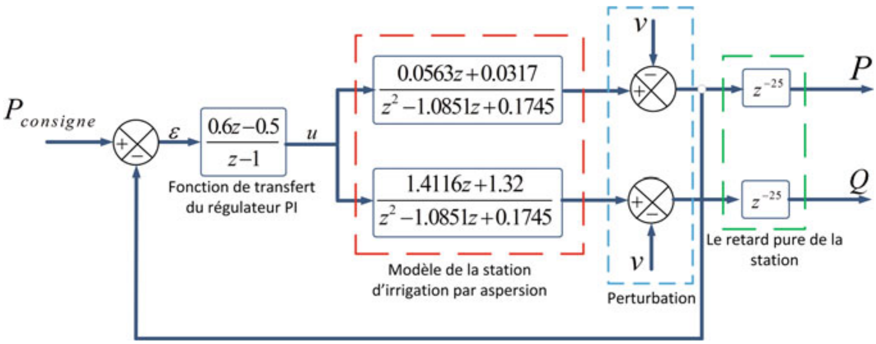


Fig. 19 Functional diagram of the system buckled with PI controller

4.2 Simulation Results of PI Controller

The result obtained by PI regulator ensures the control of the pressure because the answer follows the instruction given. In the presence of 20 % disturbance, the robustness of this technique of regulation appears in the compensation of the latter. The major disadvantage of this method of regulation resides primarily at the problem of adaptation of the controller opposite the external variations such as the extension of network of drain, the escapes, etc. (Figs. 20 and 21).

4.3 Fuzzy Logic Control of the Irrigation Station

To use the fuzzy controller (Chakchouk et al. 2014), this last must be programmed through the tool FUZZY OF MATLAB. Entries and are chosen of Gaussian form

Fig. 20 Evolution of pressure in presence of PI regulator

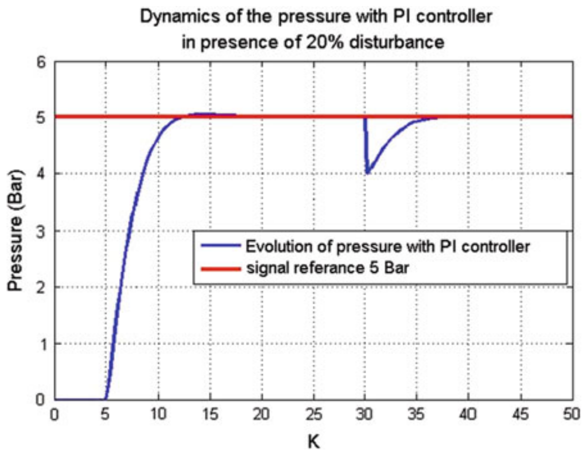
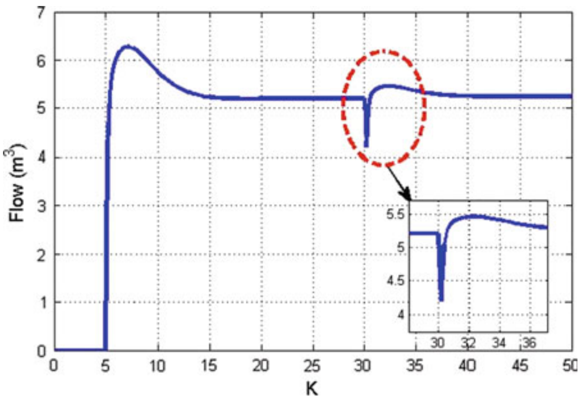


Fig. 21 Evolution of flow in presence of PI regulator



(bell) and one divided the universe of speech of each one into three sets: Z, P, and N. Thus, by using all the possible combinations, nine fuzzy rules were generated for five singletons on the level of the consequence part as it shows in Table 2 (Fig. 22). The rules can be written in the following way:

$$if\,(\varepsilon\, is\, A)\; and\; (\dot{\varepsilon}\, is\, B)\; then\; U_{cf} = S_i(\varepsilon, \dot{\varepsilon}) \tag{41}$$

One uses the method min max like engine of inferences and the centre of gravity for the defuzzification. The exit of the fuzzy controller can be written in the following form:

Table 2 Inference matrix of the fuzzy controller

	N	Z	P
N	PG	PN	NM
Z	PM	Z	NM
P	PM	NM	NG

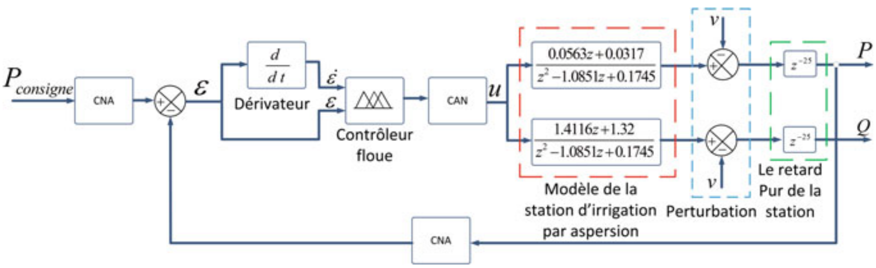


Fig. 22 Functional diagram of system buckled with a fuzzy

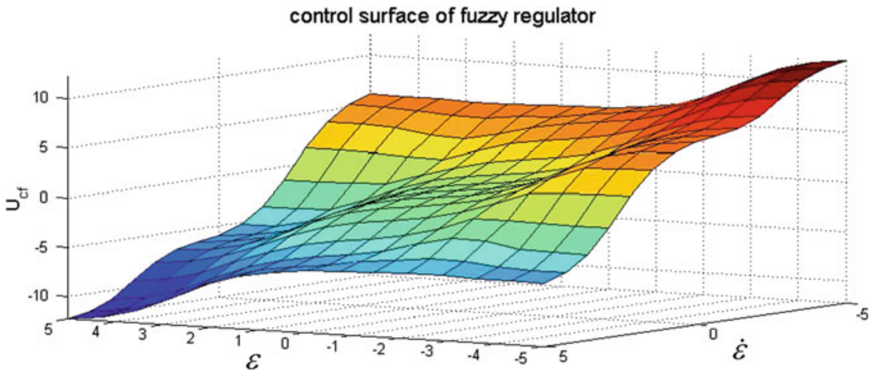


Fig. 23 The decision surface of fuzzy controller

$$S_i(\varepsilon, \dot{\varepsilon}) = \min\left(\mu_A^i(\varepsilon), \mu_B^i(\dot{\varepsilon})\right) \tag{42}$$

$$U_{cfG} = \max(S_i(\varepsilon, \dot{\varepsilon})) \tag{43}$$

The discourse universe of output U_{cf} currency in five fields (Fig. 23)

The decision surface of fuzzy controller reflect a probably smooth law of order what provides us an energy saving on the output of the fuzzy controller (Fig. 24).

4.4 Simulation Results of Fuzzy Controller

The response of the flow if the system is regulated by the fuzzy controller exceeds the maximum flow (8 m^3/h) accepted by the station of irrigation. One thus proposes to add a saturation to compensate for this going beyond (Figs. 25, 26, 27 and, 28).

4.5 Comparative Study

Taking into account the results obtained, we note that for the two examples of regulators, the fuzzy approach suggested makes it possible to obtain the best speed ratio/energy of order however the fuzzy regulation brings a static error to the evolution of the two outputs. The recourse has a profit inserted into the exit makes it possible to reduce this error (Fig. 29, Tables 3 and 4).

The fuzzy controller ensures perfectly the control of the irrigation station by sprinkling, on the other hand regulator PI used in the model appears robust from point of view stabilization in transitory mode (Fig. 30).

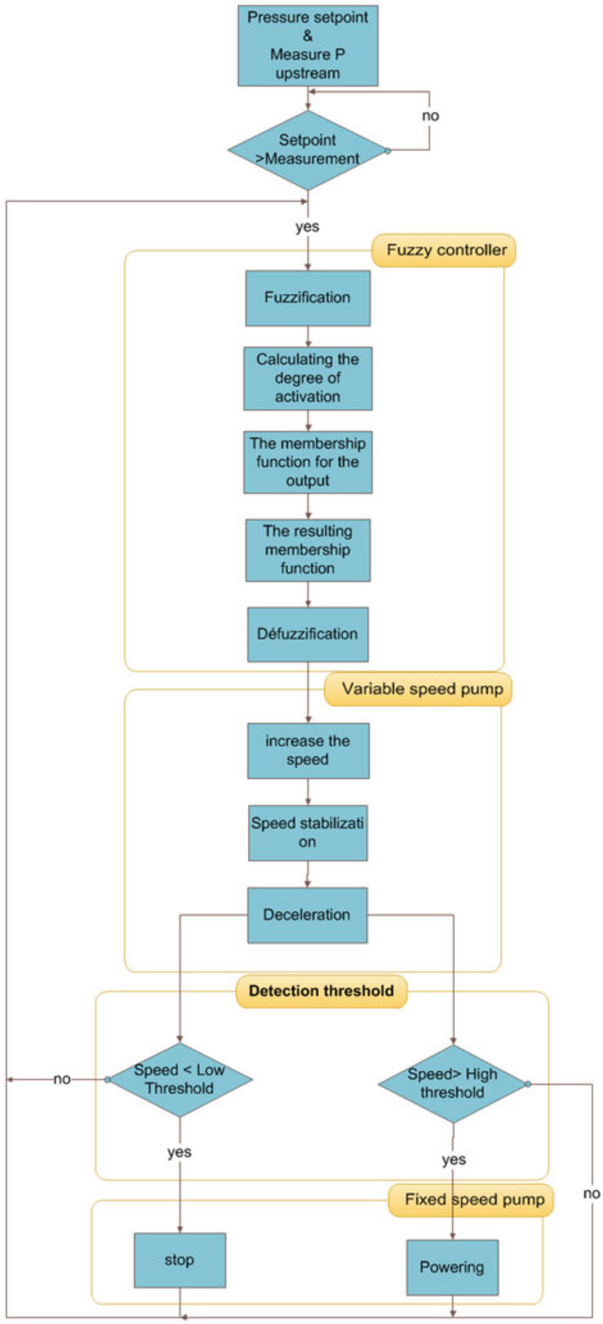


Fig. 24 Flow chart of a regulation cycle with the fuzzy controller

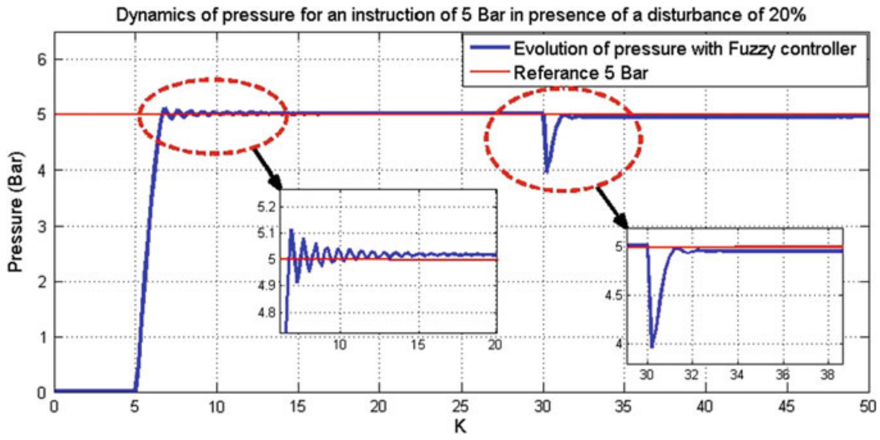


Fig. 25 Evolution of pressure with the Fuzzy controller

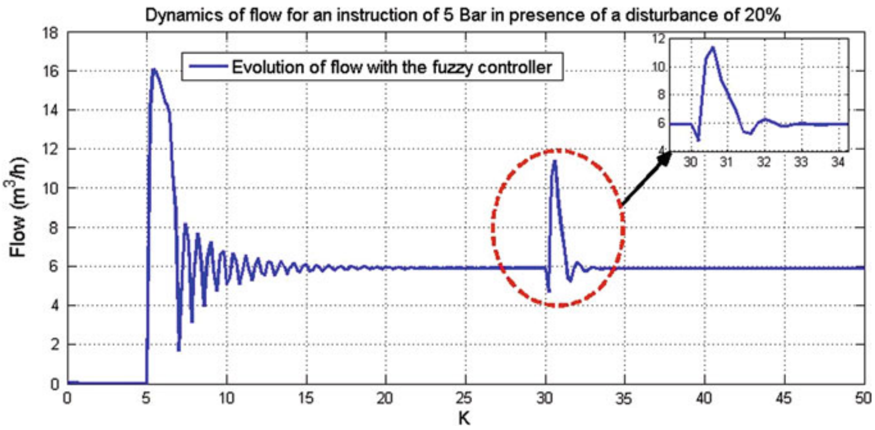


Fig. 26 Evolution of flow with the Fuzzy controller

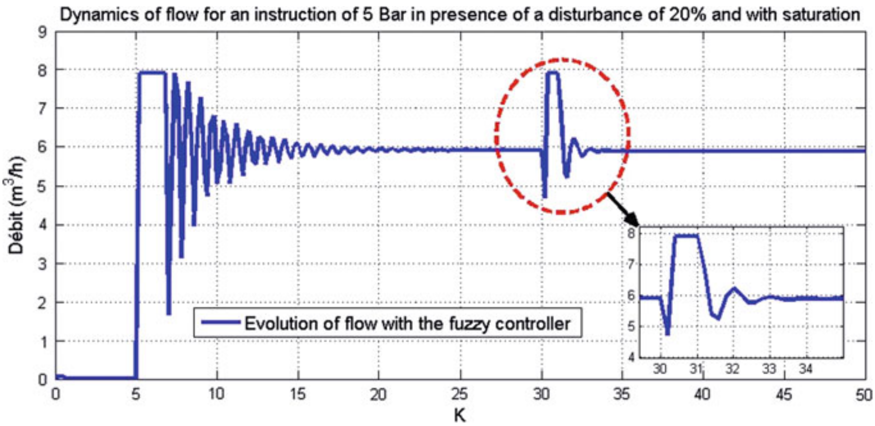


Fig. 27 Evolution of flow with the Fuzzy controller with saturation

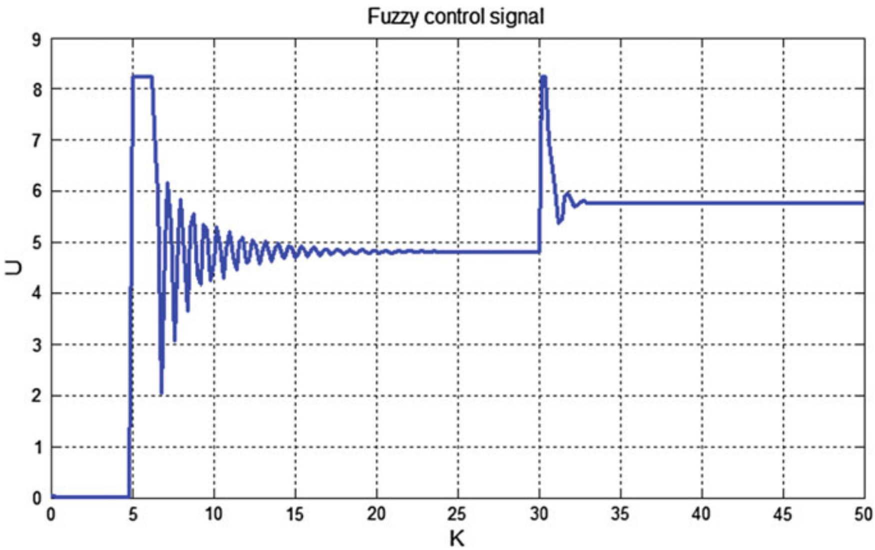


Fig. 28 Fuzzy control signal

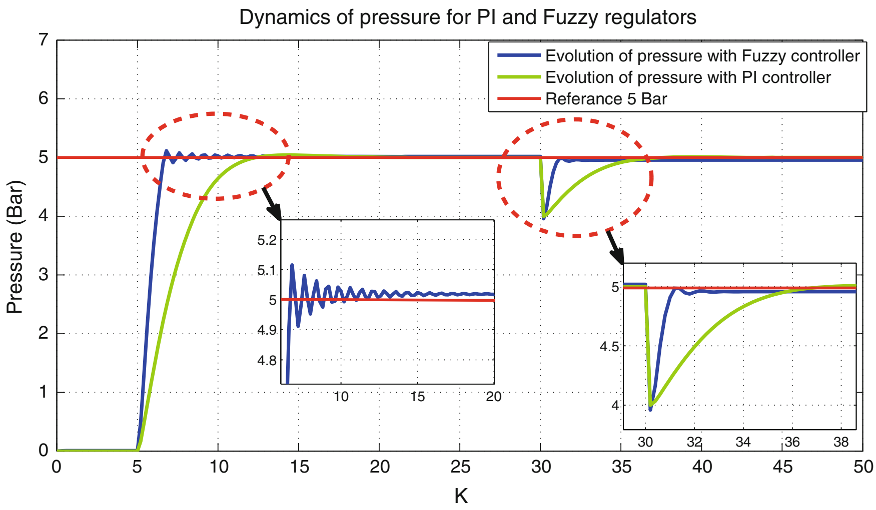


Fig. 29 Evolution of the pressure for the two types of regulators

Table 3 Comparative table enters pi and fuzzy controllers, relating to the pressure

	PI controller	Fuzzy controller
Response time at ±5%	12.6 s	6.6 s
Static error of position (in bar)	0.014	0.01

Table 4 Comparative table enters pi and fuzzy controllers, relating to flow

	PI controller	Fuzzy controller
Response time at ±5%	13.4 s	11.6 s
Static error of position (in bar)	0.8	0.088

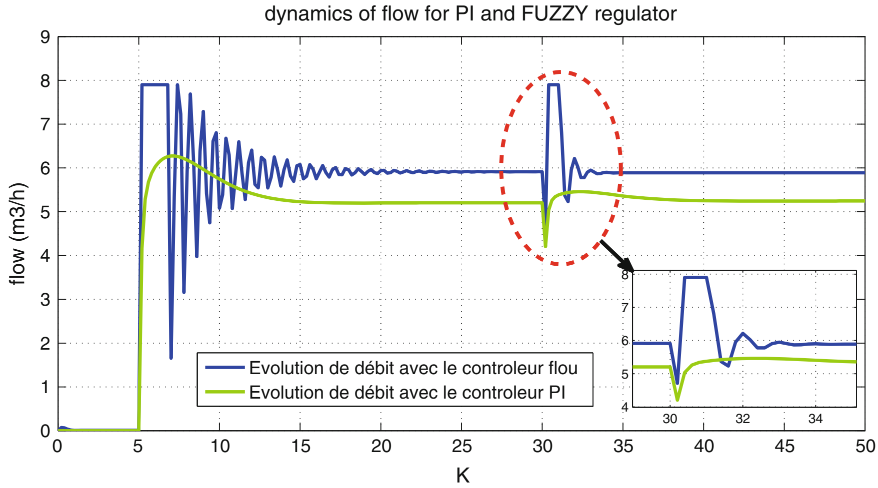


Fig. 30 Evolution of flow for the two types of regulators

5 Conclusion

In this work, we have applied the Takagi-Sugeno algorithm to a station of irrigation with sprinkling (real pumping station) and obtained real values from the station. The system is taken as a black box with outputs pressure and flow. We have modeled and identified the system by the FCM algorithm.

After obtained the T-S model we have validated curves is almost identical to the real ones. The obtained linear model gives a good description of the system behavior in the particle area of nonlinear system, and the importance of the clustering methods.

Even for the control results, the comparison between the results obtained of the two controls types (PI, Fuzzy) enables us to conclude that the fuzzy controller makes it possible to cost reduce of the water pumping.

References

Azar, A. T. (2010a). Adaptive neuro-fuzzy systems. In A.T. Azar (Ed.), *Fuzzy systems. IN-TECH,* Vienna, Austria. ISBN 978-953-7619-92-3.

Azar, A. T. (2010b). *Fuzzy systems*. Vienna, Austria: IN-TECH. ISBN 978-953-7619-92-3.

Azar, A. T. (2012). Overview of type-2 fuzzy logic systems. *International Journal of Fuzzy System Applications (IJFSA), 2*(4), 1–28.

Bertrand, A., & Moonen, M. (2012). Low complexity distributed total least squares estimation in ad hoc sensor networks. *IEEE Transactions on Signal Processing, 60*(8), 4321–4333.

Bezdek, J. (1981). *Pattern recognition with fuzzy objective function algorithms*. New York: Plenum Press.

Chakchouk, W., Zaafouri, A., & Sallami, A. (2014). Control and modelling using Takagi-Sugeno fuzzy logic of irrigation station by sprinkling. *World Applied Sciences Journal, 29*(10), 1251–1260.

Chen, J. Q., Xi, Y. G., & Zhang, Z. J. (1998). A clustering algorithm for fuzzy model identification. *Fuzzy Sets and Systems, 98*(4), 319–329.

Daneshwar, M. & Noh, N. M. (2013). *Adaptive neuro-fuzzy inference system identification model for smart control valves with static friction*. In *IEEE International Conference on Control System, Computing and Engineering (ICCSCE),* pp. 122–126, Mindeb. doi: 10.1109/ICCSCE.2013.6719944.

Duan, H., Jia, J., & Ding, R. (2011). *Two stage recursive least squares parameter estimation algorithm for output error models*. UK: Elsevier.

Eivd, M. (2005). *Digital control course*.

Grisales, V. (2007). Modélisation et commande floue de type Takagi-Sugeno appliquées a un Bioprocédé de traitement des eaux uses. (PhD thesis, Paul Sabaties University Toulouse III and Laos the Andes University, Colombie).

Gustafson, D. & Kessel, W. (1979). Fuzzy clustering with a fuzzy covariance matrix. In *Proceedings of IEEE CDC*, pp. 761–766, San Diego, CA, USA.

Jang, W., Kang, H., Lee, B., Kim, K., Shin, D., & Kim, S. (2007). Optimized fuzzy clustering by predator prey particle swarm optimization. In *IEEE Congress on Evolutionary Computation*.

Li, Z., Liang, H., and Zengjun, B. (2013). T-s fuzzy modeling method based on c-means clustering. In *International Conference on Intelligent Human-Machine Systems and Cybernetics (IHMSC)*.

Li, C. S., Zhou, J. Z., Fu, B., Kou, P., & Xiao, J. (2012). T-s fuzzy model identification with gravitational search based hyper-plane clustering algorithm. *IEEE Transaction. Fuzzy System, 20*, 305–317.

Li, C., Zhou, J., Xiang, X., Li, Q., & An, X. (2009). T-s fuzzy model identification based on a novel fuzzy c-regression model clustering algorithm. *Engineering Applications of Artificial Intelligence, 22*(4), 646–653.

Mejri, M. R., Zaafouri, A., & Chaari, A. (2013). Hybrid control of a station of irrigation by sprinkling. *International Journal of Engineering and Innovative Technology (IJEIT), 3*(1), 9–17.

Pingli, L., Yang, Y., & Wenbo, M. (2006). Random sampling fuzzy c-means clustering and recursive least square based fuzzy identification. In *Proceedings of the American control conference*.

Soltani, M., & Chaari, A. (2013). A novel weighted recursive least squares based on euclidean particle swarm optimization. *Kybernetes, 42*(2), 268–281. Emerald Group.

Soltani, M., Chaari, A., & Benhmida, F. (2012). A novel fuzzy c regression model algorithm using new measure of error and based on particle swarm optimization. *International Journal of Applied Mathematics and Computer Science, 22*(3), 617–628.

Sommer, L. (1996). *Technical catalog of irrigation station by sprinkling*. French company LEROY SOMMER.

Takagi, T., & Sugeno, M. (1985). Fuzzy identification of systems and its application to modelling and control. *IEEE Transaction, System, Man Gyber, 15*(1), 116–132.

Troudi, A., Houcine, L., & Chaari, A. (2011). New extended possibilistic c-means algorithm for identification of an electreo-hydraulic system. In *12th, International Conference, STA, ACS*.

Troudi, A., Houcine, L., & Chaari, A. (2012). Nonlinear system identification using clustering algorithm and particle swarm optimization. *Scientific Research and Essays*, 7(13):1415–1431.

Xu, Y. and Zhang, S. (2009). Fuzzy particle swarm clustering of infrared images. In *Second International Conferance on Information and Computing Science*.

Zahid, N., Abouelala, O., Limouri, M., & Essaid, A. (2001). Fuzzy clustering based on K-nearest-neighbours rule. *Fuzzy Sets Systems*, *120*:239–247.