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Contributed Paper

Real-Time Fuzzy Adaptive Control

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In the paper a new fuzzy adaptive cancellation control scheme is presented and compared with model-reference adaptive control. The basic part of the fuzzy adaptive cancellation controller is the inverse fuzzy model, which is given in the form of a fuzzy relational matrix. The comparison has been evaluated by implementation in a heat exchanger and a real hydraulic pilot plant, which exhibit nonlinearity and time-variance. It is shown that in the case of processes which exhibit relatively simple dynamics, and are at the same time nonlinear and time-varying, the adaptive fuzzy cancellation controller is superior to the classical model-reference adaptive control.

Keywords: Fuzzy control, identification, adaptive control

1. INTRODUCTION

In some industrial control problems, the parameters of the controlled process either are poorly known or vary during operation. In such cases, the use of an adaptive control technique is generally necessary to obtain a high-performance control system. Many solutions have been proposed to make control systems adaptive. Model-reference adaptive systems evolved in the late 1950's (Isermann *et al.*, 1992). The main innovation of such systems is the presence of a reference model which specifies the desired dynamics of the closed-loop system. The reference model can also be implicitly included into the closed-loop system by means of a cancellation principle. The cancellation principle of model-reference control has been used to develop fuzzy adaptive systems.

As with conventional adaptive controllers, adaptive fuzzy controllers can also be categorized into direct and indirect types. An "indirect" type of adaptive system means that adaptation is based on the process model obtained using identification. In the case of direct adaptive systems, no model of the process is needed. The first approaches to fuzzy adaptive control were of the direct type, proposed by Procyk and Mamdani (1979); after that some of the indirect type appeared, proposed by Czogala and Pedrycz (1981), Moore and Harris (1992), and Graham and Newell (1988, 1989).

The indirect type of fuzzy adaptive control is based on fuzzy identification, which can be expressed by a rule-type model or by a relational matrix model. The proposed method of inverse model identification can be applied to stable and phase-minimal processes.

Many practical processes exhibit simple dynamics which can be approximately described by a first-order model. However, the parameters of the processes can vary significantly and rapidly with time. Such processes will be referred to here as *mutable* processes with single dynamics.

In the paper, a comparison is made between fuzzy adaptive cancellation controllers based on the inverse fuzzy relational model, and conventional model-reference adaptive systems. Both adaptive schemes have been tested on real mutable processes with single dynamics, i.e. a heat exchanger and a hydraulic pilot plant, which exhibit nonlinear characteristics and whose parameters vary significantly during operation. This was the main motivation

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for implementing an adaptive technique by extending some well-known concepts from adaptive and fuzzy theory. According to this, the algorithm of the fuzzy adaptive cancellation controller, based on the recursive fuzzy identification of the inverse matrix model, has been developed and implemented in real hydraulic and heat-exchanger plants. For this purpose, on-line recursive fuzzy identification, represented by means of the fuzzy relational matrix, has been developed. The fuzzy relational matrix of the observed process is obtained on the basis of the fuzzified process input and output variables.

2. FUZZY CANCELLATION ADAPTIVE CONTROLLER

The general form of the fuzzy cancellation adaptive system developed here is presented in Fig. 1. It consists of recursive fuzzy identification of the inverse process model and the model-reference part, which is given as a filter. The fuzzy model of the process is given in the form of an inverse process model, i.e. as an input error model. This model is used in the fuzzy cancellation controller scheme. In the next two subsections, the relational matrix identification and the fuzzy cancellation controller will be given.

2.1. The fuzzy relational matrix model identification

Fuzzy logic appears to be a very promising approach in process automation. Fuzzy modelling or identification has become a very important area. To model or identify the process means finding a set of fuzzy if-then rules with well-defined attributes, that can describe the given I/O behaviour of the process. In recent years, many different approaches to fuzzy identification have been proposed in the literature (e.g. Tong, 1976; Czogala and Pedrycz, 1981; Pedrycz, 1984; Takagi and Sugeno, 1985; Sugeno and Tanaka, 1991).

Mutable processes, even those with single dynamics, exhibit behaviour which is very difficult to represent in mathematical form. An alternative approach to the modelling of such systems is given by the identification of the fuzzy model. Due to the adaptive character of the whole system, it is necessary to obtain information about the process parameters at each time instant. For real-time implementation, time constraints require a compact and fast recursive fuzzy identification technique. The relationship (mapping) between the fuzzy sets that are defined in the domain of model inputs and those defined in the domain of model outputs is given in matrix form.

The fuzzy identification algorithm used in this paper is based on the fuzzy relational matrix model with crisp output variables given in the literature (Takagi and Sugeno, 1985; Sugeno and Tanaka, 1991; Pfeiffer, 1994).

Suppose the rule-base of a fuzzy system is as follows:

$$R_i\text{: IF } x_1 \textit{ is } A_i \textit{ and } x_2 \textit{ is } B_i \text{ THEN } y=r_i \tag{1}$$

$$i=1,\ldots,N \tag{2}$$

where x_1 and x_2 are input variables of the process, y is an output variable, A_i, B_i are fuzzy sets characterized by their membership functions and r_i are the crisp values. Such a very simplified fuzzy model can be regarded as a collection of several linear models, applied locally in the fuzzy regions, defined by the rule premises. The idea behind this kind of modelling is close to the well-known concept of gain scheduling.

Rule-premises are formulated as fuzzy AND relations on the Cartesian product set $X=X_1\times X_2$, and several rules are connected by logical OR. Fuzzification of a crisp value x_1 produces a column vector

$$\mu(x_1)=[\mu_{A_1}(x_1),\mu_{A_2}(x_1),\ldots,\mu_{A_m}(x_1)]^T \tag{3}$$

and similarly for a crisp value x_2. The degrees of fulfillment of all possible AND combinations of the rule premises are calculated and written into matrix **S**. If the algebraic product is used as an AND operator, this matrix can be directly obtained by multiplication:

$$\mathrm{S}=\mu_1\otimes\mu_2^T=\mu_1\cdot\mu_2^T. \tag{4}$$

The dimension of matrix $\mathbf{S}(m\times n)$, which actually represents the structure of the model, depends on the dimensions of the input fuzzy sets $\mu_1(m\times 1)$ and $\mu_2(n\times 1)$.

In order to apply a standard least-squares method to estimate the parameters r_{ij}, the vectors **s** and **r** are formed from **S** and **R** respectively:

$$\mathbf{s}=(s_{11}s_{12}\cdots s_{1n}\cdots s_{m1}s_{m2}\cdots s_{mn})^T$$
$$\mathbf{r}=(r_{11}r_{12}\cdots r_{1n}\cdots r_{m1}r_{m2}\cdots r_{mn})^T. \tag{5}$$

A crisp output value y is computed by a simplified algorithm for singletons as a weighted mean value (Center of Singeltons):

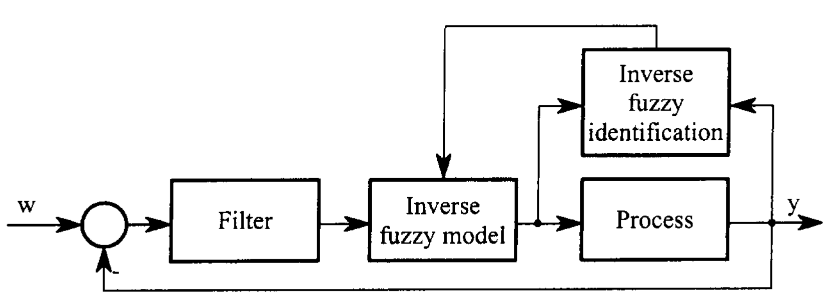

Fig. 1. The general scheme of the fuzzy cancellation adaptive system.

$$y=\frac{\sum_{i=1}^{n}\sum_{j=1}^{m} s_{ij}r_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{m} s_{ij}}, \tag{6}$$

$$s_{ij}=\min\,(\mu_{A_i}(x_1),\mu_{B_j}(x_2)). \tag{7}$$

Using these vectors, (6) is rewritten:

$$y=\frac{\mathbf{s}^T\cdot\mathbf{r}}{\mathbf{s}^T\cdot\mathbf{I}} \tag{8}$$

where $\mathbf{I}$ defines the vector of ones of the same dimension $(n\cdot m\times 1)$ as $\mathbf{s}$ and $\mathbf{r}$. The elements r_{ij} are estimated on the basis of observations obtained at equidistant time intervals by measuring the process input and output. A system of linear equations is constructed from the upper equations for the time intervals $t=t_1$, $t=t_2$, ..., $t=t_N$, where N represents the number of samples for the I/O data, which are given at equidistant time intervals:

$$\begin{bmatrix}\mathbf{s}^T(t_1)\\ \mathbf{s}^T(t_2)\\ \vdots\\ \mathbf{s}^T(t_N)\end{bmatrix}\cdot\mathbf{r}=\begin{bmatrix}\mathbf{s}^T(t_1)\cdot\mathbf{I}y(t_1)\\ \mathbf{s}^T(t_2)\cdot\mathbf{I}y(t_2)\\ \vdots\\ \mathbf{s}^T(t_N)\cdot\mathbf{I}y(t_N)\end{bmatrix}. \tag{9}$$

The system is of the form:

$$\Psi\cdot\mathbf{r}=\Omega \tag{10}$$

with a known nonsquare matrix Ψ and a known vector Ω The solution of this overdetermined system is obtained by taking the pseudo-inverse as an optimal solution of vector $\mathbf{r}$ in a least-squares sense:

$$\mathbf{r}=(\Psi^T\Psi)^{-1}\Psi^T\Omega \tag{11}$$

where Ψ stands for a fuzzified data matrix with dimension $N\times(n\cdot m)$ and Ω has dimension $N\times 1$.

In the case of more than two input variables, matrices $\mathbf{S}$ and $\mathbf{R}$ are no longer matrices, but both become a tensor, defined in the total product space of the inputs.

Adaptive systems require recursive fuzzy identification to obtain on-line information about the actual behaviour of the process, which is necessary to adapt the whole system in a desired way. The elements r_{ij} are estimated on the basis of observations obtained at equidistant time intervals by measuring the process input and output. For real-time implementation, the process parameters should be estimated, and the whole algorithm calculated, in the time between two samples. This restriction might be a serious problem. If the process parameters are time-varying, the last sample gives more information on the current behaviour of the process than previous samples did, so exponential weighting should be used. The method of recursive fuzzy identification with exponential weighting is based on the loss function

$$J(\hat{\mathbf{r}})=\sum_{k=1}^{N}\lambda^{N-k}(y(k)-\mathbf{s}_n^T(k)\hat{\mathbf{r}}(k))^2, \tag{12}$$

where $y(k)$ is the current value of the process output, $\mathbf{s}_n^T(k)$ is the normalised fuzzy data vector, $\hat{\mathbf{r}}(k)$ is the current value of the estimated fuzzy relational vector, and λ is the forgetting factor. The proper value of the forgetting factor is chosen between 0.95 and 0.98, as proposed by Isermann *et al.* (1992). Optimizing the loss function (12) the recursive fuzzy identification with exponential weighting is obtained in the following form

$$\hat{\mathbf{r}}(k+1)=\hat{\mathbf{r}}(k)+\mathbf{K}(k)(y(k+1)-\mathbf{s}_n^T(k)\hat{\mathbf{r}}(k))$$

$$\mathbf{K}(k)=\mathbf{P}(k)\mathbf{s}_n(k+1)[\lambda+\mathbf{s}_n^T(k+1)\mathbf{P}(k)\mathbf{s}_n(k)]^{-1}$$

$$\mathbf{P}(k+1)=\frac{1}{\lambda}[\mathbf{I}-\mathbf{K}(k)\mathbf{s}_n^T(k+1)]\mathbf{P}(k).$$

When there is no *a priori* information on the initial values of the estimated parameters, the initial value of the matrix $\mathbf{P}(0)$ has to be chosen sufficiently large, and the initial values of the estimated fuzzy relational vector parameters are set to zero:

$$\mathbf{p}(0)=\alpha\mathbf{I},\ \alpha\gg 1, \tag{13}$$

$$\hat{\mathbf{r}}(0)=\mathbf{0}. \tag{14}$$

The application of recursive fuzzy identification requires continuous monitoring and supervision of several parameters. The identification algorithm may be started in the closed loop after specifying free parameters and setting the initial conditions for parameter estimation. These problems are connected with the start-up procedure and pre-identification. Another problem is the persistent excitation in the closed loop. All these problems are discussed in the section on supervision and coordination.

2.2. Fuzzy adaptive cancellation controller based on a fuzzy relational matrix

The fuzzy cancellation controller is designed using the same considerations as the conventional cancellation controller—to ensure the desired closed-loop response (Isermann *et al.*, 1992). It consists of a cancellation (adaptive) part, which is realized as a fuzzy inverse model of the process, and a noncancellation (nonadaptive) part, which is determined using the reference model in the same way as in the case of the conventional cancellation controller. The fuzzy cancellation controller is described by the following equations:

$$\frac{U_{\mathrm{aux}}(z)}{E(z)}=\frac{G_{\mathrm{m}}(z)}{1-G_{\mathrm{m}}(z)} \tag{15}$$

$$u_{\mathrm{f}}(k)=\mathbf{s}_n^T(k)\cdot\hat{\mathbf{r}}_{\mathrm{c}}(k) \tag{16}$$

where $G_{\mathrm{m}}(z)$ represents the desired model of the closed-loop system, $\mathbf{s}_n^T$ the fuzzified vector of the $u_{\mathrm{aux}}(k)$ and $u_{\mathrm{aux}}(k-1)$,

$\hat{\mathbf{r}}_c$ the current estimate of the fuzzy relational vector of the inverse process, and $e(k)$ the error between the reference signal $w(k)$ and the output signal $y(k)$. $U_{aux}(z)$ and $E(z)$ are their Z-transforms. The scheme of the fuzzy cancellation adaptive system is presented in Fig. 2. It could be concluded that the adaptive mechanism is realised through inverse process modelling.

The algorithm of the fuzzy cancellation adaptive controller exhibits some advantages in comparison with the conventional adaptive technique. These advantages are based on fuzzy identification, which enables the identification of the nonlinear process dynamics, and also implicitly describes the operating point of the process.

2.3. Supervision and coordination

The implementation of parameter-adaptive control requires an additional supervision and coordination system, to eliminate or avoid all expected or unexpected changes in the operating conditions of the controlled process in the adaptive control loop. Such changes may result in unacceptable or unstable control behaviour of the parameter-adaptive controller. Therefore, continuous monitoring and supervision of the parameter-adaptive control-loop functions are required.

Both tasks, supervision and coordination, can be realized as a third-level feedback in the adaptive control loop. The tasks that are involved in supervision and coordination comprise recognition of faulty functions, diagnosis and monitoring (Isermann *et al.*, 1992). The main purpose of the supervision and coordination level is to eliminate (or at least reduce) the causes of faulty functioning of the whole adaptive system. No general supervision and coordination levels exist, and for each application the realization of online supervision and coordination is unique and depends on the main goal, effort, computation time available, intentions and overall supervisory philosophy.

In the case of fuzzy cancellation adaptive control, the first problem arises with setting the initial fuzzy relational vector of the inverse model. In this case, the initial fuzzy relational vector available for the controller design procedure either does not exist, or has poor confidence. In order to avoid malfunctioning of the whole adaptive system, a pre-identification phase is employed, within the supervision and coordination level, to obtain the initial fuzzy relational vector of the inverse model. Pre-identification in the case of the fuzzy adaptive control is calculated in a closed loop, using a robust PI controller instead of the fuzzy cancellation controller. When the identified fuzzy process model adequately matches the dynamic input–output behaviour of the real plant, control can be given to the fuzzy cancellation controller. The switch is made when the system fulfills the following equation:

$$e_u(k) \leq 0.05u(k). \tag{17}$$

The input error $e_u(k)$ is defined as the difference between the input process signal $u(k)$ and the estimated input process signal $\hat{u}(k)$, calculated on the basis of the inverse fuzzy process model

$$e_u(k) = |u(k) - \hat{u}(k)|. \tag{18}$$

The main problem of closed-loop identification in the case of fuzzy adaptive cancellation control is that it cannot be guaranteed that the resulting process input signal is persistently exciting, for the process model parameter estimation to match process behaviour accurately enough. Therefore, no useful information about process dynamics can be gained from the measured process input and output signal values. This results in linearly dependent rows of the information matrix **P**. In this case, the identification problem becomes insoluble.

Implementing the recursive version of least squares or extended least squares, the problem of nonpersistent excitation of the process is indicated by an increasing variance of all parameter estimates. This results in wrong values of parameter estimates and information matrix trace divergence. The problem is known as "bursting". A simple

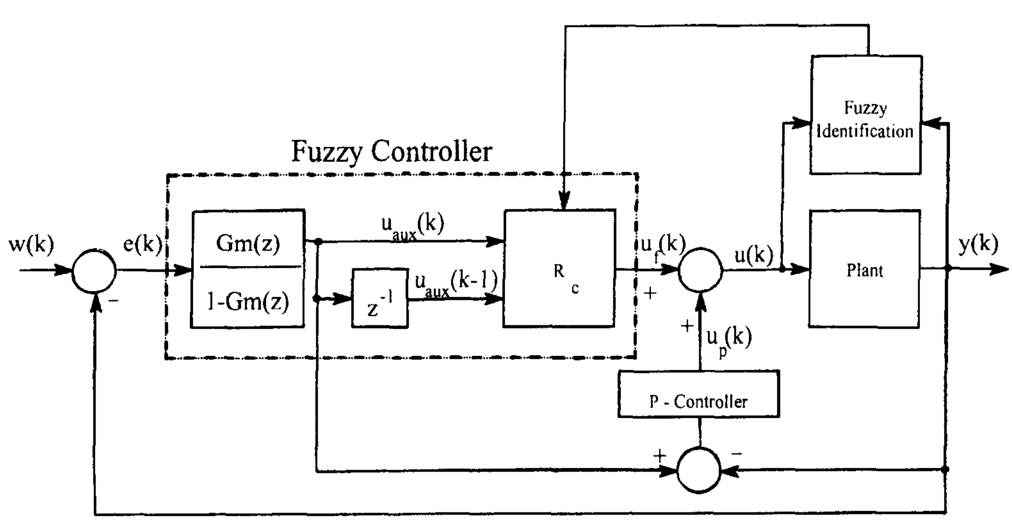

Fig. 2. The scheme of the fuzzy cancellation adaptive system.

action to avoid influence on the parameter estimates is an automatic switch-off of the identification method according to the eigenvalues of matrix **P**, or the trace of the same matrix. This principle is also used in the case of the fuzzy relational matrix identification.

A very important part of supervision in the case of fuzzy cancellation adaptive control is the P controller which controls the difference between the variable on the inverse model input $u_{aux}(k)$ and process output $y(k)$. In the ideal case, both variables should be equal. When the controller action of an implemented fuzzy cancellation controller is too weak or too strong (poor estimation of the process parameters), an additional supervision controller is needed. The input of the P-supervisory controller is the difference between the variables $y(k)$ and $u_{aux}(k)$, and the output is $u_p(k)$ which forms (together with the output from the fuzzy cancellation controller $u_f(k)$) the control signal $u(k)$ of the process. Figure 2 shows the fuzzy cancellation controller with the P-supervisory controller in the closed loop.

3. ADAPTIVE CONTROL OF THE HEAT-EXCHANGER PILOT PLANT

The adaptive approach discussed above has been implemented in a real temperature-control plant, which consists of a plate heat exchanger, through which hot water from an electrically heated reservoir is continuously circulated in a counter-current flow to cold process fluid (cold water). The thermocouples are located in the inlet and outlet flows of the exchanger; both flow rates can be visually monitored. Power to the heater may be controlled by time-proportioning control, using the external control loop. The flow of the heating fluid can be controlled by the proportional motor-driven valve. A schematic diagram of the plant is shown in Fig. 3.

The temperature plant is a process where the variables are significantly dependent on the spatial coordinates at a given moment in time, so the dynamics of the heart of the process—the heat exchanger—could be represented by the following set of partial differential equations

$$\frac{\partial T_1(z,t)}{\partial t} + v_1 \frac{\partial T_1(z,t)}{\partial z} = k_1[T_s(t) - T_1(z,t)] \qquad (19)$$

$$\frac{\partial T_s(t)}{\partial t} = k_2[T_2(z,t) - T_s(t)] - k_2[T_s(t) - T_1(z,t)]$$

$$\frac{\partial T_2(z,t)}{\partial t} - v_2(t) \frac{\partial T_2(z,t)}{\partial z} = k_1[T_s(t) - T_2(z,t)]$$

where $T_1(z,t)$, $T_2(z,t)$ and $T_s(z,t)$ represent the temperatures of the cold water, heating water and the iron wall respectively, $v_1(t)$ and $v_2(t)$ the velocities of the cold and heating water, and k_1 and k_2 constants which include the heat-transfer coefficients and the physical dimensions of the heat exchanger.

The solution of the set of (19) would yield the mathematical model of the the heat exchanger, with the input defined by the current velocity of the heating water $v_2(t)$ and the output defined as the outlet temperature T_1 of the cold water. In order to obtain a simple model of the heat exchanger, theoretical modelling would be very difficult because of the nonlinear character of the third equation in the set, (19). Furthermore, the heat exchanger is just one part of the plant, so the sensors and the actuators should also be modelled. The motor-driven valve exhibits strongly nonlinear and time-varying behaviour.

System modelling based on conservational laws and first principles would be a very difficult, expensive and time-consuming task. Instead, fuzzy identification of the process is used. Although the process is very complex, it could be presented as a model with approximately first-order dynamics with a small time delay, with significantly time-varying

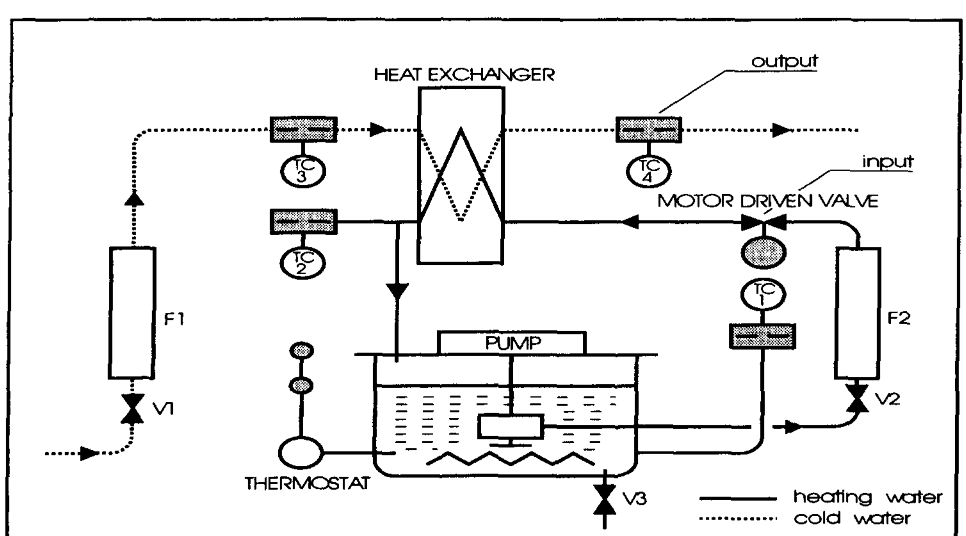

Fig. 3. The heat-exchanger pilot plant.

parameters and nonlinearities according to the operating point.

During the experiments, some values of the physical parameters (velocity v_1 and the temperature T_2 at the inlet of the exchanger), which are supposed to be constant, were changing. These variations have a great influence on the gain and on the dominant time constant of the process. The period of the first 400 s was used for the pre-identification in the closed loop, using the robust PI controller. Afterwards, the fuzzy adaptive controller was switched on.

The results of fuzzy adaptive control are shown in Fig. 4, where the output $y(t)$ and the reference model output $y_m(t)$ are presented.

After 2780 s, a change was made to the valve position in the cold-water circuit. The position was changed by approximately 25%. After a transient phase, the process output followed the reference model properly.

For an evaluation of the results, the experiment was repeated under the same conditions using a conventional globally stable model-reference adaptive control scheme (Isermann *et al.*, 1992). The output of the closed loop $y(t)$ and the reference model output $y_m(t)$ are shown in Fig. 5.

The initial conditions in this case have been set near to the assumed values, because otherwise the algorithm diverges.

The model-following is much better in the case of fuzzy adaptive control, due to the ability of the fuzzy model to cope with the nonlinearities.

4. ADAPTIVE CONTROL OF A HYDRAULIC PILOT PLANT

The fuzzy adaptive cancellation control approach has also been implemented in a hydraulic pilot plant. The hydraulic pilot plant consists of a reservoir, filled through an inlet at the top of the reservoir and emptied at the bottom of the reservoir through a manually adjustable valve. Circulation of the liquid is obtained using an electric pump.

The dynamics of the pilot plant can be described by the following differential equation:

$$\tau(h)\frac{\mathrm{d}h}{\mathrm{d}t}+h=K_z(h)\Phi+K_p(h,p_v)p_v(h), \tag{20}$$

where $\tau(h)$ is the time constant of the process and depends on the liquid level h in the reservoir, $p_v(h)$ is the valve pressure and $K_z(h)$ and $K_p(h,p_v)$ are constants which depend on the process operating point. The operating point can be changed by the manually adjustable valve.

The electric pump operates in the range between 0 and 10 V, and has a nonlinear, time-variant characteristic. The nonlinearity is a dead zone of 3 V, which means that the pump starts to operate if the input is greater than 3 V, and a curved dependance between the voltage and the flow. The characteristic of the pump changes with time, so the measured nonlinearity will vary. Thus the controlled process is a mutable process. Another nonlinear effect arises when the pump input signal becomes greater than 8 V. In this range, disturbances in the pump operation accrue, caused by air bubbles. The pump characteristic can be symbolically described by the following equation:

$$\Phi(k)=f(k,u)(k)). \tag{21}$$

The combination of (20) and (21) yields the controlled process, with the input defined by the voltage applied to the pump $u(k)$ and the output defined as the liquid level $h(k)$.

During the experiments, the position of the manually adjustable valve was changed. This change has a great influence on the gain and on the dominant time constant of

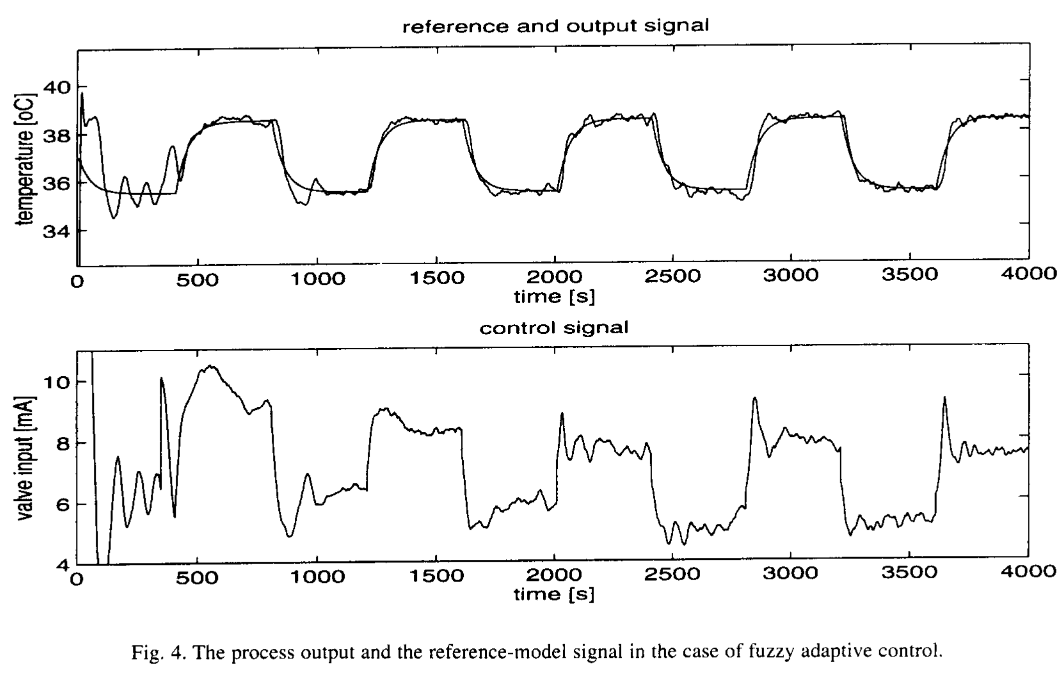

Fig. 4. The process output and the reference-model signal in the case of fuzzy adaptive control.

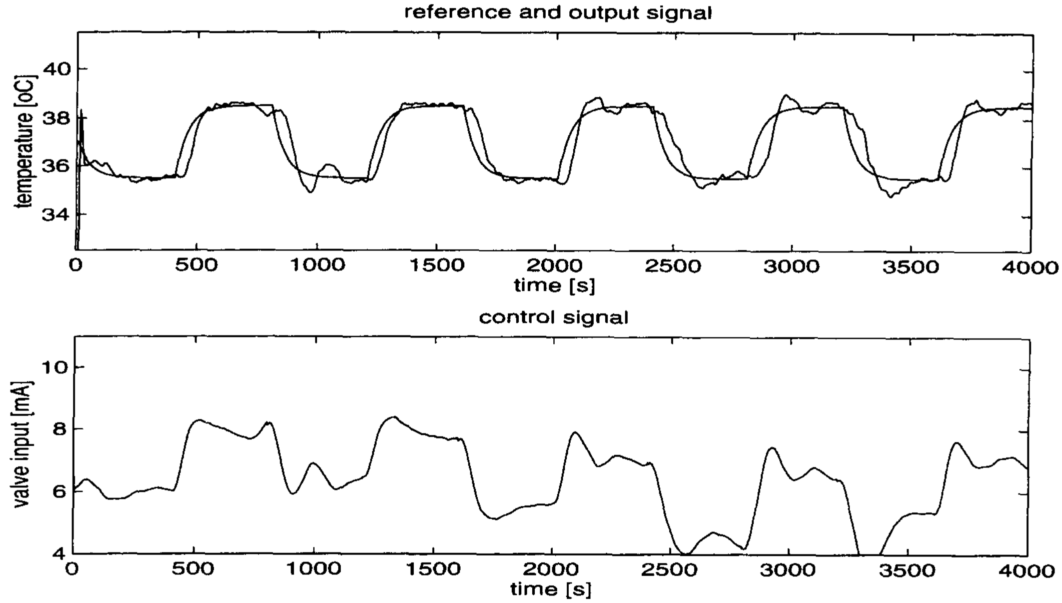

Fig. 5. The process output and the reference-model signal in the case of the model-reference adaptive control.

the process. The manually adjustable valve was half-open at the beginning. At the time instant t=200 s, the fuzzy adaptive controller was switched on. The process characteristic was changed as follows: at the time instant t=700 s, the valve was opened to the value 5/6, at t=1300 s the valve was closed to 1/2, and at t=1500 s to 1/6.

The same experiment has been realized using both controllers. In the case of fuzzy adaptive control, huge oscillations at the beginning are due to the initially wrong settings of the controller parameters. Also huge over and undershoots are observed at t=1500 s, when closing the valve to 1/6. After the transient phase, the process output more or less follows the model-reference output. The discrepancies are due to the approximation of the process by the first-order plant, which is obviously not justified, even in a single operating point. The period of the first 200 s is used for pre-identification in the closed loop, and during this period the system is controlled using the robust PI controller. Figure 6 shows the output process signal $y(t)$, the prescribed-model output signal $y_m(t)$ and the control signal $u(k)$ for the fuzzy adaptive cancellation controller. The prescribed model has been chosen equal to the reference model of the model-reference adaptive control.

The oscillations after switching on the fuzzy adaptive cancellation controller are smaller than the initial oscillations of the model-reference adaptive control. Also, the

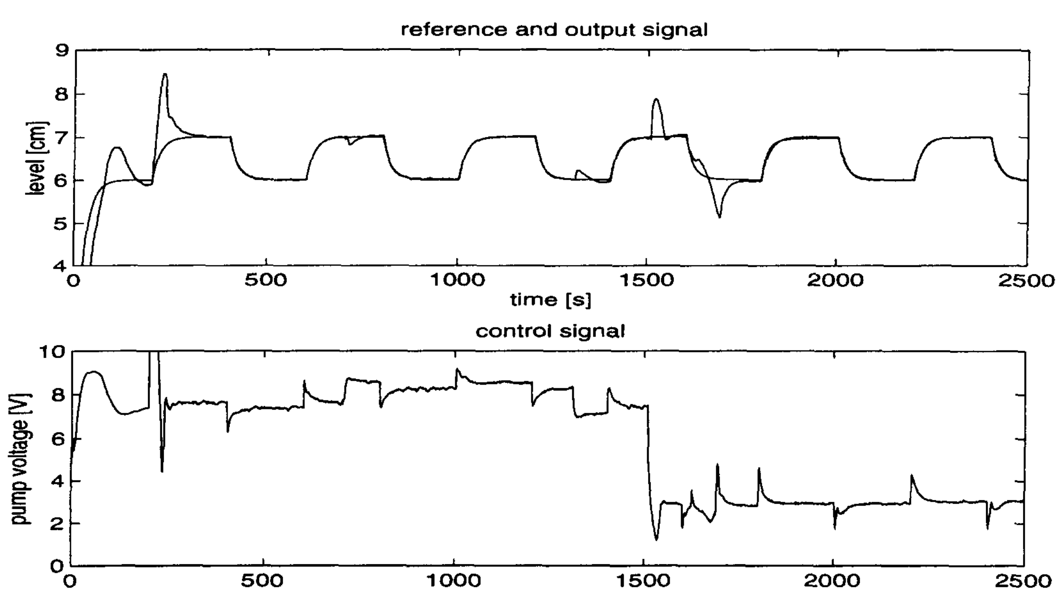

Fig. 6. The process output, the prescribed model output and the control signal in the case of the fuzzy adaptive control.

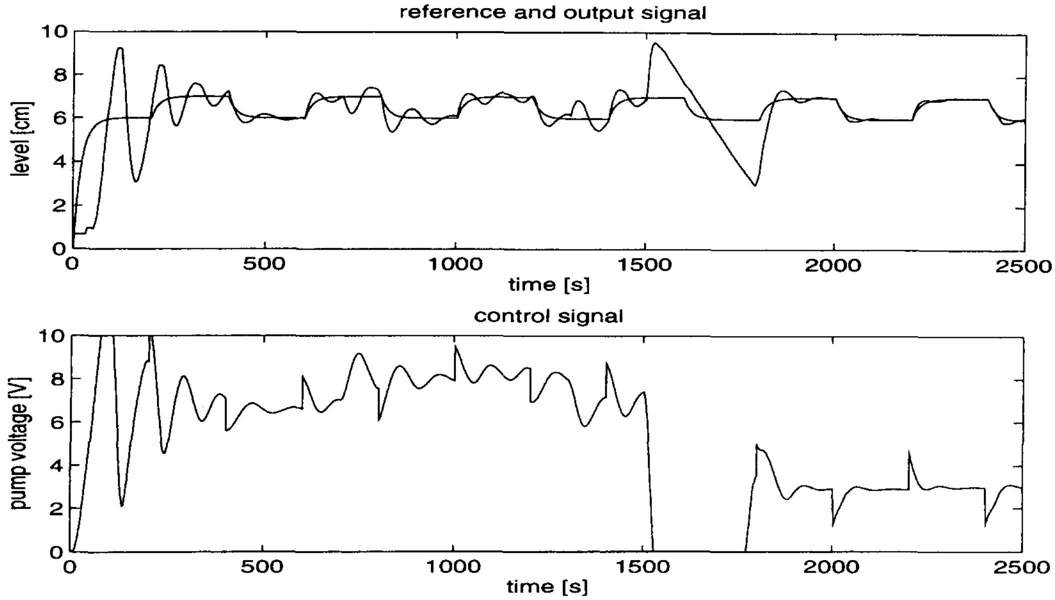

Fig. 7. The process output, the reference model and the control signal in the case of the model-reference adaptive control.

oscillations when changing the operating point are smaller, due to the supervisory P controller. The model-following is better than in the case of the model-reference adaptive controller, due to ability of the fuzzy model to describe nonlinearities.

The results for the continuous model-reference adaptive control are shown in Fig. 7. This shows the output process signal $y(t)$, the reference-model output signal $y_m(t)$ and the control signal $u(k)$.

All the experiments were realized using the *Simulink* program package to simulate the dynamic systems. This is a part of the *Matlab* program package, in the *Windows* environment. The communication between program package and the *Burr–Brown* process interface has been also realized inside the Simulink package with a *Mex* file written in the *C* programming language.

5. CONCLUSION

In the paper, a fuzzy adaptive cancellation controller is presented. The development of a new fuzzy adaptive scheme was motivated by the unsatisfactory results obtained using conventional model-reference adaptive techniques. Regarding the real-time experiments on the temperature and hydraulic plants, which exhibit nonlinear and time-varying characteristics, it was found that the novel algorithm introduces faster convergence and better performance in the presence of nonlinearity and unmeasured dynamics, due to the improved fuzzy identification method. The proposed approach seems to be usable in the case of time-varying or nonlinear systems with simple dynamics. In such cases, the proposed algorithm gives some advantages in comparison to the conventional model-reference adaptive technique, resulting in better system performance.

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