Int. J. of Computers, Communications & Control, ISSN 1841-9836, E-ISSN 1841-9844
Vol. V (2010), No. 2, pp. 179-192

Evolved Fuzzy Control System for a Steam Generator

D. Hossu, I. Făgărăşan, A. Hossu, S.S. Iliescu

Daniela Hossu, Ioana Făgărăşan, Andrei Hossu, Sergiu St. Iliescu
University Politehnica of Bucharest
Automatic Control and Industrial Informatics
No.313 Splaiul Independentei, District 6, Code 060042, Bucharest, Romania
E-mail: andone_dana@yahoo.com, dana@aii.pub.ro, ioana@shiva.pub.ro

Abstract:
Poor control of steam generator water level is the main cause of unexpected shutdowns in nuclear power plants. Particularly at low powers, it is a difficult task due to shrink and swell phenomena and flow measurement errors. In addition, the steam generator is a highly complex, nonlinear and time-varying system and its parameters vary with operating conditions. Therefore, there is a need to systematically investigate the problem of controlling the water level in the steam generator in order to prevent such costly reactor shutdowns. The objective of this paper is to design, evaluate and implement a water level controller for steam generators based on a fuzzy model predictive control approach. An original concept of modular evolved control system, seamless and with gradual integration into the existent control system is proposed as base of implementation of the presented system.
Keywords: evolved control, nonlinear system, fuzzy model, predictive control.

1 Introduction

Poor control of the steam generator water level in the secondary circuit of a nuclear power plant can lead to frequent reactor shutdowns. Such shutdowns are caused by violation of safety limits on the water level and are common at low operating power where the plant exhibits strong non-minimum phase characteristics.

Difficulties on designing a steam generator (SG) level controller arise from the following factors:

- reverse dynamics, or non-minimum phase behavior due to swell and shrink effects,
ticularly at low power,
- changes in plant dynamics with operating power,
- dynamics uncertainties,
- corrupted feed-water flow measurement signal with biased noises.

Particularly it is difficult to control automatically a steam generator water level during transient period or at low power less than 15% of full power because of its dynamic characteristics.

Various approaches have been reported in the literature: an adaptive PID level controller using a linear parameter varying model to describe the process dynamics over the entire operating power range [12]; LQG controllers with "gain-scheduling" to cover the entire operating range [15]; a hybrid fuzzy-PI adaptive control of drum level, a model predictive controller to identify the operating point at each sampling time and use the plant model corresponding to this operating point as the prediction model [14].

A nonlinear physical model with a complexity that is suitable for model-based control has been presented by Aström and Bell [5]. The model describes the behavior of the system over a wide operating range. A model of the steam generator water level process in the form of a transfer function, determined based on first-principles analysis and expert experience has been presented in [30]. A detailed nonlinear model based on the lumped parameter approach for system modules, developed for a typical PWR power plant has been presented in [1]. In the paper trained neural networks are used to predict certain system parameters of the plant for a number of different power demand histories. Paper [17] presents a self organizing fuzzy logic controller for the water level control of a steam generator.

With the advent of the current generation of high-speed computers, more advanced control strategies not limited to PI/PID, can be applied [11], [18], [20], [23]. Model predictive control (MPC) is one such controller design technique, which has gained wide acceptance in process control applications. Model predictive control has three basic steps: output prediction, control calculation and closing the feedback loop [6], [7], [16]. In this paper, we apply MPC techniques to develop a framework for systematically addressing the various issues in the SG level control problem. The Takagi-Sugeno fuzzy model representation often provides efficient and computationally attractive solutions to a wide range of modeling problems capable to approximate nonlinear dynamics, multiple operating modes and significant parameter and structure variations [22], [24]. This paper deals with Takagi-Sugeno (T-S) fuzzy models because this type of model have a good capability for prediction and can be easily used to design model-based predictive controllers for nonlinear systems [9].

The paper includes simulations of typical operating transients in the SG.

A new concept of modular advanced control system designed for a seamless and gradual integration into the target systems is presented. The system is designed in such a way to improve the quality of monitoring and control of the whole system. The project targets the large scale distributed advanced control systems with optimum granularity architecture.

2 Fuzzy Model

Fuzzy models have become one of the most well established approaches to non-linear system modeling since they are universal approximations which can deal with both quantitative and qualitative (linguistic) forms of information [8], [9], [21], [26], [27], [28], [29]. These models can broadly be divided into three classes: Linguistic Models - so-called Mamdani-type Models, Fuzzy Relational Models, and Takagi-Sugeno (TS) Models [14]. Both linguistic and fuzzy relational models are linguistically interpretable and can incorporate prior qualitative knowledge provided by experts [25]. However, when linguistic knowledge extraction is not the main purpose of modeling, like in many dynamic system identification and control problems, the use of TS models becomes particularly adequate since they are able to accurately represent a wide class of nonlinear systems using a relatively small number of parameters. In a nutshell, TS models perform an interpolation of local models, usually linear or affine in their arguments, by means of a fuzzy inference mechanism. Their functional rule base structure is well-known to be intrinsically favorable for control applications.

The TS model representation often provides efficient and computationally attractive solutions to a wide range of modeling problems capable to approximate nonlinear dynamics, multiple operating modes and significant parameter and structure variations. The ability of such model to capture the dynamics of a large class of nonlinear plants has been investigated extensively in the literature [13].

In this paper, we apply MPC techniques to develop a framework for systematically addressing the various issues in the SG level control problem. This paper deals with Takagi-Sugeno (T-S) fuzzy models because of their capability to approximate a large class of static and dynamic nonlinear systems. In T-S modeling methodology, a nonlinear system is divided into a number of nearly linear subsystems. A quasi-linear empirical is developed by means of fuzzy logic for each subsystem. The whole process behavior is characterized by a weighted sum of the outputs from all quasi-linear fuzzy implication. The methodology facilitates the development of a nonlinear model that is essentially a collection of a number of quasi-linear models regulated by fuzzy logic. It also provides an opportunity to simplify the design of model predictive control.

The system is divided into a number of linear or nearly linear subsystems. By Takagi-Sugeno's modeling methodology a fuzzy quasi-linear model has to be developed for each subsystem. In such a model, the cause-effect relationship between control u and output y at the sampling time n is established in a discrete time representation. Each fuzzy implication is generated based on a system *step response* [3, 4, 10].

$$\begin{gathered} IF\ y(n)\ is\ A_0^i,\ y(n-1)\ is\ A_1^i,\ \ldots,\ y(n-m+1)\ is\ A_{m-1}^i, \\ and\ u(n)\ is\ B_0^i,\ u(n-1)\ is\ B_1^i,\ \ldots,\ u(n-l+1)\ is\ B_{l-1}^i \\ THEN\ y^i(n+1) = y(n) + \sum_{j=1}^{T} h_j^i\,\Delta u(n+1-j) \end{gathered} \tag{1}$$

where:

A_j^i	fuzzy set corresponding to output *y(n-j)* in the i^{th} fuzzy implication
B_j^i	fuzzy set corresponding to input *u(n-j)* in the i^{th} fuzzy implication
h_j^i	impulse response coefficient in the i^{th} fuzzy implication
T	model horizon
$\triangle u(n)$	difference between *u(n)* and *u(n-1)*

A complete fuzzy model for the system consists of p fuzzy implications. The system output *y(n+1)* is inferred as a weighted average value of the outputs estimated by all fuzzy implications

$$y(n+1) = \frac{\sum_{j=1}^{p} \mu^j y^j(n+1)}{\sum_{j=1}^{p} \mu^j} \tag{2}$$

where

$$\mu^j = \wedge_i A_i^j \wedge_k B_k^j \tag{3}$$

considering

$$\omega^j = \frac{\mu^j}{\sum_{j=1}^{p} \mu^j} \tag{4}$$

then

$$y(n+1) = \sum_{j=1}^{p} \omega^j\, y^j(n+1) \tag{5}$$

3 Fuzzy Model Predictive Control

3.1 Problem formulation

The design goal of a fuzzy model predictive control is to minimize the predictive error between an output and a given reference trajectory in the next N_y steps through the selection of N_u step optimal control policies.

The optimization problem can be formulated as:

$$min_{\Delta u(n),\, \Delta u(n+1),\, \ldots,\, \Delta u(n+N_u)}\, J(n) \tag{6}$$

$$J(n) = \sum_{i=1}^{N_y} \mu_i(\hat{y}(n+i) - y^r(n+i))^2 + \sum_{i=1}^{N_u} v_i \Delta u(n+i)^2 \tag{7}$$

where:

μ_i and v_i	are the weighting factors for the prediction error and control energy;
$\hat{y}(n+1)$	i^{th} step output prediction;
$y^r(n+1)$	i^{th} step reference trajectory;
$\Delta u(n+i)$	i^{th} step control action.

The weighted sum of the local control policies gives the overall control policy:

$$\Delta u(n+i) = \sum_{j=1}^{p} \omega^j \Delta u^j(n+i) \tag{8}$$

Substituting (2) and (8) into (7) yields (9)

$$J(n) = \sum_{i=1}^{N_y} \mu_i \left(\sum_{j=1}^{p} \left(\omega^j \left(\hat{y}^j(n+i) - y^r(n+i) \right) \right) \right)^2 + \sum_{i=0}^{N_u-1} v_i \left(\sum_{j=1}^{p} \omega^j \Delta u^j(n+i) \right)^2 \tag{9}$$

To simplify the computation, an alternative objective function is proposed as a satisfactory approximation of (9) [10].

$$\widetilde{J}(n) = \sum_{j=1}^{p} \left(\left(\omega^j \right)^2 \left(\sum_{i=1}^{N_y} \mu_i \left(\hat{y}^j(n+i) - y^r(n+i) \right)^2 + \sum_{i=0}^{N_u-1} v_i \, \Delta u^j(n+i)^2 \right) \right) \tag{10}$$

The optimization problem can be defined as:

$$min_{\Delta u(n),\, \Delta u(n+1),\, \ldots,\, \Delta u(n+N_u-1)} \widetilde{J}(n) = min_{\Delta u(n),\, \Delta u(n+1),\, \ldots,\, \Delta u(n+N_u-1)} \sum_{j=1}^{p} \left(\omega^j \right)^2 \widetilde{J^j}(n) \tag{11}$$

where

$$\widetilde{J^j}(n) = \sum_{i=1}^{N_y} \mu_i \left(\hat{y}^j(n+i) - y^r(n+i) \right)^2 + \sum_{i=0}^{N_u-1} v_i \left(\Delta u^j(n+i) \right)^2 \tag{12}$$

Using the alternative objective function (12), we can derive a controller by a hierarchical control design approach.

3.2 Controller design

1. *Lower Layer Design*: For the j^{th} subsystem, the optimization problem is defined as follows:

$$min_{\Delta u(n),\, \Delta u(n+1),\, \ldots,\, \Delta u(n+N_u-1)} \widetilde{J^j}(n) \tag{13}$$

   subject to:

$$R_j : \begin{cases} IF\ y(n+k-1)\ is\ A_0^j,\ \ldots,\ y(n+k-m)\ is\ A_{m-1}^j \\ THEN\ y^j(n+k) = y^j(n+k-1) + \sum_{j=1}^{T} h_i^j \Delta u(n+k-i) + \varepsilon^j(n+k-i) \end{cases} \tag{14}$$

   Where $\varepsilon^j(n+k-1)$ serves for system coordination and it is determined at the upper layer.

2. *Upper Layer Design*: The upper layer coordination targets the identification of globally optimal control policies through coordinating $\varepsilon^j(n+k-1)$ for each local subsystem.

3. *System Coordination*: From the lower layer, the local information of output and control is transmitted to the upper layer. At the upper layer, the error variables are evaluated as: $\varepsilon^j(n+k-1) = y(n+k-1) - y^j(n+k-1)$. These values will be compared with those for the same error variables calculated in the last iteration. If

$$\sum_{j=1}^{p}\sum_{k=1}^{N_y}\left|e^j(n+k-1)-\varepsilon^j(n+k-1)\right| > \beta$$

then the control policies are not optimal and need to be modified at the lower layer; else an optimal control action is found.

The whole design is decomposed into the derivation of p local controllers. The subsystems regulated by those local controllers will be coordinated to derive a globally optimal control policy. The objective function defined in (12) can be rewritten in a matrix form:

$$\widetilde{J^j}(n) = \left(\hat{Y}_+^j(n) - Y^r(n)\right)^T W_1^j \left(\hat{Y}_+^j(n) - Y^r(n)\right)_+ + \left(\Delta U_+^j(n)\right)^T W_2^j \left(\Delta U_+^j(n)\right) \tag{15}$$

where:

$$\hat{Y}_+^j(n) = \left(\hat{y}^j(n+1)\hat{y}^j(n+2)\ldots\hat{y}^j(n+N_y)\right)^T \tag{16}$$

$$Y^r(n) = (y^r(n+1)y^r(n+2)\ldots y^r(n+N_y))^T \tag{17}$$

$$\Delta U_+^j(n) = \left(\Delta u^j(n)\Delta u^j(n+1)\ldots\Delta u^j(n+N_u-1)\right)^T \tag{18}$$

$$W_1^j = diag\left\{\mu_1^j,\ \mu_2^j,\ \ldots,\ \mu_{N_y}^j\right\} \tag{19}$$

$$W_2^j = diag\left\{v_1^j,\ v_2^j,\ \ldots,\ v_{N_u}^j\right\} \tag{20}$$

The N_y - step prediction of the output by the j^{th} FI can be rewritten as follows:

$$\hat{Y}_+^j(n) = A^j\Delta U_+^j(n) + Y(n) + P^j(n) + E_+^j(n) \tag{21}$$

where:

$$A^j = \begin{bmatrix} a_1^j & 0 & 0 & \ldots & 0 \\ a_2^j & a_1^j & 0 & \ldots & 0 \\ a_3^j & a_2^j & a_1^j & \ldots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{N_y}^j & a_{N_y-1}^j & a_{N_y-2}^j & \ldots & a_{N_y-N_u+1}^j \end{bmatrix} \tag{22}$$

$$a_i^j = \sum_{k=1}^{i} h_k^j \tag{23}$$

$$Y(n) = (y(n)\ y(n)\ \ldots y(n)\ )^T \tag{24}$$

$$P^j(n) = \left(P_1^j(n)\ P_2^j(n)\ \ldots P_{N_y}^j(n)\ \right)^T \tag{25}$$

$$E_+^j(n) = \left(0\sum_{k=1}^{2}\varepsilon^j(n+k-1)\ \cdots \sum_{k=1}^{N_y}\varepsilon^j(n+k-1)\right)^T \tag{26}$$

$$P_i^j(n) = \sum_{k=1}^{i}\sum_{l=k+1}^{T} h_l^j \Delta u(n+k-l) \tag{27}$$

The resulting control policy for the j^{th} subsystem can be derived as:

$$\widetilde{J}^j(n) = \left(\Delta U_+^j(n)\right)^T \left(A^{j^T} W_1^j A^j + W_2^j\right) \Delta U_+^j(n) +$$

$$+\left(\Delta U_+^j(n)\right)^T A^{j^T} W_1^j Z^j(n) + \left(Z^j(n)\right)^T W_1^j A^j \Delta U_+^j(n) + \left(Z^j(n)\right)^T W_1^j Z^j(n) \quad (28)$$

where:

$$Z^j(n) = Y(n) - Y^r(n) + P^j(n) + E_+^j(n) \quad (29)$$

Minimizing (26) yields:

$$\frac{\delta \widetilde{J}^j(n)}{\delta \Delta U_+^j(n)} = 2(A^{j^T} W_1^j A^j + W_2^j)\Delta U_+^j(n) + 2A^{j^T} W_1^j Z^j(n) = 0 \quad (30)$$

The control law by the j^{th} FI can be identified as:

$$\left(\Delta U_+^j(n)\right)^* = -K^j Z^j(n) \quad (31)$$

where K^j is:

$$K^j = \left(A^{j^T} W_1^j A^j + W_2^j\right)^{-1} A^{j^T} W_1^j \quad (32)$$

The optimal local control policies at the lower layer are identified through optimization, the optimal global control policies can be accordingly derived at the upper layer.

$$\Delta U_+(n) = (\Delta u(n) \Delta u(n+1) \dots \Delta u(n+N_u-1))^T \quad (33)$$

3.3 Parameter Tuning

In controller design, the difficulty encountered is how to quickly minimize the upper bound of the objective function so that the control actions can force a process to track a specified trajectory as close as possible. There has no rigorous solution to the selection of optimal control horizon *(N_u)* and prediction horizon *(N_y)*. The model horizon is selected so that $T\Delta t \geq$ open loop settling time.

The ranges of weighting factors W_1^j and W_2^j can be very wide, the importance is their relative magnitudes. The following three-step procedure to tune the weighting factors is proposed:

(a) Select a value for W_1 and assign it to all local controllers. Determine W_2^j independently for each local controller in order to minimize the objective function for that subsystem

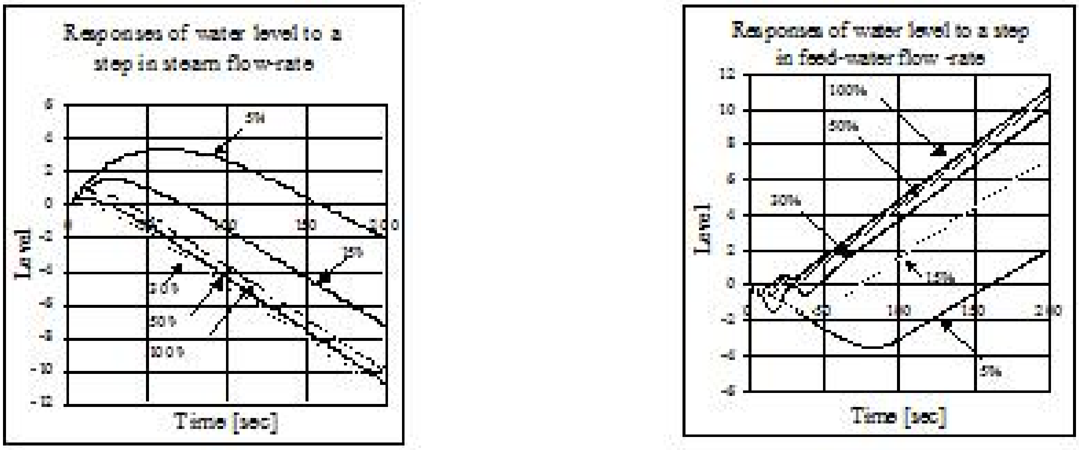
(b) Identify the largest W_2 and assign it to all subsystems.

(c) Examine the system's closed-loop dynamic performance. If not satisfied, then reduce the value of W_2 gradually until the desirable dynamic performance is identified.

3.4 Simulations

Process Modeling

The main problem in setting up a signal flow diagram for a level controlled system in a SG can be found in the inhomogeneous contents of the SG. The filling consists of water at boiling temperature, pervaded by steam bubbles. Since the volume fraction of the steam bubbles is quite considerable, the mean specific weight of the contents is very strongly dependent on the proportion of steam. This, of



(a) (b)

Figure 1: Responses of water level at different operating power (indicated by %) to (a) a step in steam flow-rate. (b) a step in feed-water flow-rate.

course, means that the steam content also strongly influences the level in the SG. The steam content itself depends, in turn, on the load factor, on the changes in feed-water flow, and on feed-water temperature.

The presence of steam below the liquid level in the SG causes the *shrink-and-swell* phenomenon that in spite of an increased supply of water, the water level initially falls. Fig. 1 shows responses of the water level to steps in feed-water and steam flow-rates at different operating powers. For generating the responses, it was used the power dependent linear parameter varying model identified by Irving [12]. At low loads the non-minimum phase behavior is much more pronounced.

The changing process dynamics and the inverse response behavior significantly complicate the design of an effective water level control system. A solution to this problem is to design local linear controllers at different points in the operating regime and then applies gain-scheduling techniques to schedule these controllers to obtain a globally applicable controller.

Consider a step in feed-water flow rate at 5% operating power because of the strong inverse response. For this system, a fuzzy convolution model consisting of four fuzzy implications is developed as follows:

For j=1 to 4
R^j: if $y_{D_{al}}$ (n) is A^j
then $y^j_{D_{al}}(n+1) = y^j_{D_{al}}(n) + \sum_{i=1}^{200} h^j_{D_{al}} u(n+1-i)$

In order to define the fuzzy sets we propose the following strategy: $D_{al_1} = min(y^1_{D_{al}}) \cdot K_{D_{al_1}}$, $D_{al_2} = min(y^2_{D_{al}}) \cdot K_{D_{al_2}}$, $D_{al_3} = min(y^3_{D_{al}}) \cdot K_{D_{al_3}}$, $D_{al_4} = min(y^4_{D_{al}}) \cdot K_{D_{al_4}}$ where $K_{D_{al_1}} = 0.2$, $K_{D_{al_2}} = 0.9$, $K_{D_{al_3}} = 0.9$, $K_{D_{al_4}} = 0.2$. are selected in order to obtain a characteristic as close as possible to the open loop response of water level at 5% operating power to a step in feed-water flow-rate.

Fig. 2 shows the impulse response coefficients for $y^1_{D_{al}}$, $y^2_{D_{al}}$, $y^3_{D_{al}}$, $y^4_{D_{al}}$ subsystems and Fig. 3 shows the definition of fuzzy sets A^1, A^2, A^3 and A^4. Consider a step in steam flow rate at 5% operating power. For this system, a fuzzy convolution model consisting of fourfuzzy implications is developed as follows:

For j=1 to 4
R^j: if y_{D_0} (n) is A^j
then $y^j_{D_0}(n+1) = y^j_{D_0}(n) + \sum_{i=1}^{200} h^j_{D_0} u(n+1-i)$

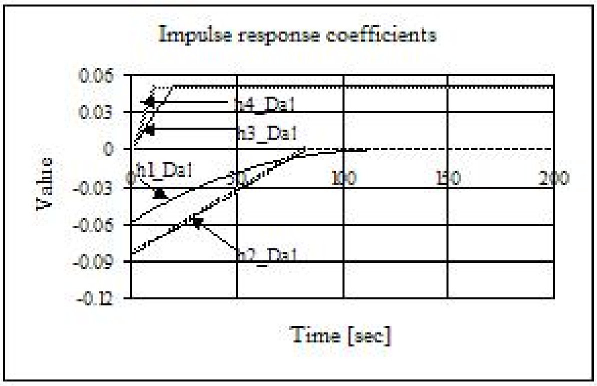


Figure 2: The impulse response coefficients for $y^1_{D_{al}}$, $y^2_{D_{al}}$, $y^3_{D_{al}}$, $y^4_{D_{al}}$ subsystems.

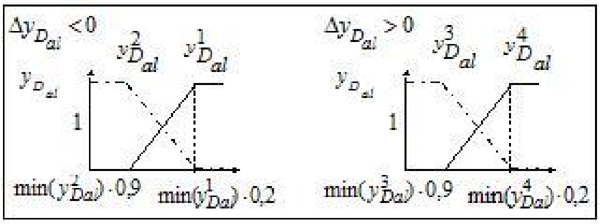


Figure 3: Definition of fuzzy sets A^1, A^2, A^3 *and* A^4 for FI R^1, R^2 ,R^3 *and* R^4 respectively.

In order to define the fuzzy sets we propose the following strategy: $D_{o_1} = max(y^1_{D_o}) \cdot K_{D_{o_1}}$,$D_{o_2} = max(y^2_{D_o}) \cdot K_{D_{o_2}}, D_{o_3} = max(y^3_{D_o}) \cdot K_{D_{o_3}}, D_{o_4} = max(y^4_{D_o}) \cdot K_{D_{o_4}}$ where $K_{D_{o_1}} = 0.4$, $K_{D_{o_2}} = 0.9$, $K_{D_{o_3}} = 0.9$, $K_{D_{o_4}} = 0.6$ are selected in order to obtain a characteristic as close as possible to the open loop response of water level at 5% operating power to a step in steam flow-rate.

Fig. 4 shows the impulse response coefficients for $y^1_{D_o}$, $y^2_{D_o}$, $y^3_{D_o}$, $y^4_{D_o}$ subsystems, Fig. 5 shows the definition of fuzzy sets A^1, A^2, A^3 and A^4.

Controller Design

The goal in this paper is to study the use of the feed-water flow-rate as a manipulated variable to maintain the SG water level within allowable limits, in the face of the changing steam demand resulting from a change in the electrical power demand.

Frequent reactor shutdowns are caused by violation of safety limits on the water level and are

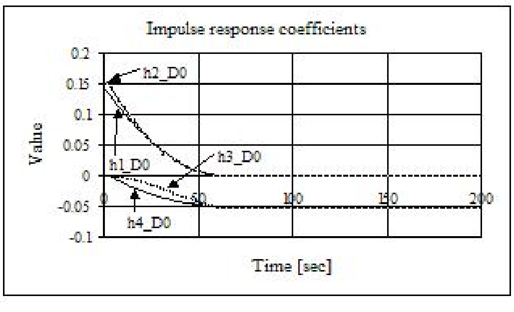


Figure 4: The impulse response coefficients for $y^1_{D_o}$, $y^2_{D_o}$, $y^3_{D_o}$, $y^4_{D_o}$ subsystems.

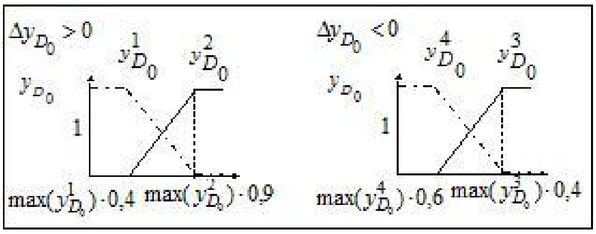


Figure 5: Definition of fuzzy sets A^1, A^2, A^3 *and* A^4 for FI R^1, R^2 ,R^3 *and* R^4 respectively.

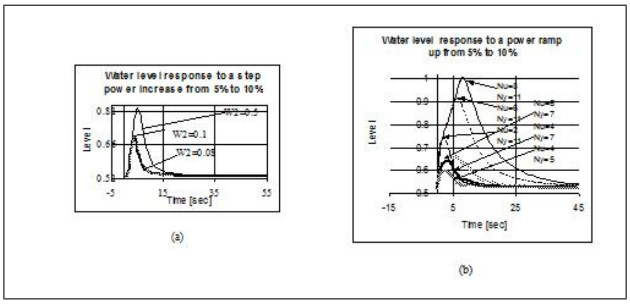


Figure 6: Normalized water level setpoint.

common at low operating power where the plant exhibits strong non-minimum phase characteristics.Fig. 6 shows the normalized water level setpoint and safety limits.

The goal of fuzzy model predictive control is to minimize the predictive error between an output and a given reference trajectory in the next N_y (prediction horizon) steps through the selection of N_u (control horizon) step optimal control policies.

Using the alternative objective function (12), we can design a controller by a hierarchical control design approach.

The whole design is decomposed into the derivation of 4 local controllers. The subsystems regulated by those local controllers will be coordinated to derive a globally optimal control policy. The objective function defined in (12) can be rewritten in a matrix form as follows:

$$\widetilde{J}^j(n) = \left(\hat{Y}_+^j(n) - Y^r(n)\right)^T W_1^j \left(\hat{Y}_+^j(n) - Y^r(n)\right)_+ + \left(\Delta U_+^j(n)\right)^T W_2^j \left(\Delta U_+^j(n)\right) \tag{34}$$

where:

$$\hat{Y}_+^j(n) = \left(\hat{y}_{D_{al}}^j(n+1)\hat{y}_{D_{al}}^j(n+2)\dots\hat{y}_{D_{al}}^j(n+N_y)\right)^T \tag{35}$$

$$Y^r(n) = (y^r(n+1)y^r(n+2)\dots y^r(n+N_y))^T \tag{36}$$

$$y^r(n) = y^{ref}(n) - y_{D_0}(n) \tag{37}$$

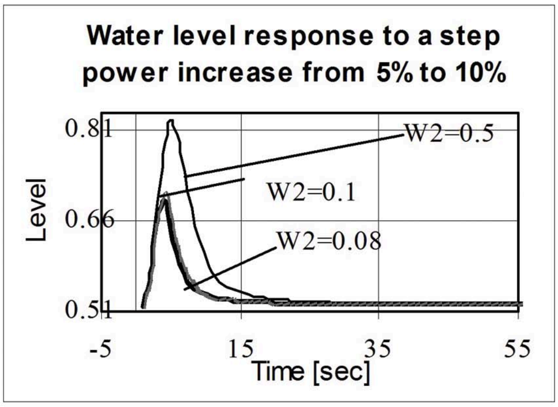
$$\Delta U_+^j(n) = \left(\Delta u^j(n)\Delta u^j(n+1)\dots\Delta u^j(n+N_u-1)\right)^T \tag{38}$$

$$W_1^j = diag\left\{\mu_1^j,\, \mu_2^j,\, \dots,\, \mu_{N_y}^j\right\} \tag{39}$$

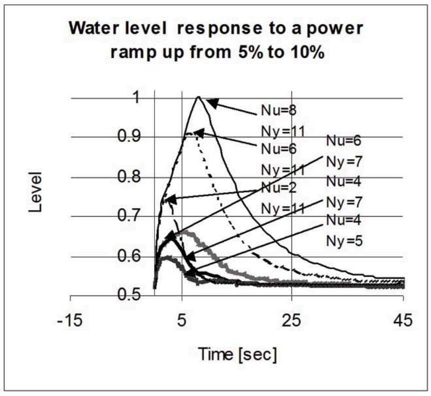
$$W_2^j = diag\left\{v_1^j,\, v_2^j,\, \dots,\, v_{N_u}^j\right\} \tag{40}$$

The simulations are organized around two different power transients:

- a step-up in power from 5% to 10% (Fig. 7(a));
- a ramp-up in power from 5% to 10% (Fig. 7(b)).



a)



b)

Figure 7: Water level response to (a) a step power increase from 5% to 10% (Nu=2, Ny=3, W1=1). (b) a power ramp up from 5% to 10% (W2=0.1, W1=1).

The model horizon is $T = 200$. Increasing N_y results in a more conservative control action that has a stabilizing effect but also increases the computational effort.

The computational effort increases as N_u is increased. A small value of N_u leads to a robust controller.

We can see that the performance is not strongly affected by the presence of the feed-water inverse response, only a slight oscillation is visible in the water level response. All local controllers are used all the time. This means that there is no switch from one local controller to the other in operation. The system output is infered as a weighted average value of the outputs of all subsystems. On the other hand, the overall control policy to the process under control is the weighted sum of all local control policies. This kind of design not only eliminates the controller switch problem and thus possible system instability, but also provides a much more smooth control performance in process operation. The performance is not strongly affected by the presence of the feed-water inverse response, only a slight oscillation is visible in the water level response. The FMPC responses are very satisfactory and not very sensitive to changes in tuning parameters.

3.5 Evolved Controller Client/Server Architecture

An original concept of modular *evolved* control system, seamless and with gradual integration into the *primary* control system is proposed. The target systems are the *large scale distributed control systems* with *optimum granularity architecture*. The aim of the application is to integrate the concepts of *evolved control algorithms, portability of software modules, real time characteristics of the application*. We propose an approach of a *seamless integration* of the evolved control modules into an existing control system. The first part of the life cycle phases of the new control system, from conception to validation stage, the new control system lives hiding in the shadow of the control system it will replace, and after validation the old system will be replaced by the new one. The identification, modeling, control and validation stages of the life cycle of the system, will be done *on-line* (the new system uses a real image of the I/O process data), without affecting the existing control system.

Because of high level of *interconnectivity between system components*, it is necessary to provide the *highest independence between communication modules on one-hand and the control modules on the other hand*. In order to obtain high ability of integration, the communication modules have to cover the widest possible area of industrial communication interfaces and protocols.

One item of the application is to offer a *unified API of extended generality and extendibility in order* *to unify access and information retrieval from various wireless and wired technology and communication interfaces* (RS 232, RS 485, fieldbus: Profibus / Interbus, Ethernet IP, TCP/IP, etc). Applications could properly adapt to changes in the network connections. The design and implementation of a solution *to hide the embedded communication network problems from the application system programmers* is included.

A software package for *evolved control* includes a method based on *fuzzy model predictive control*. By using the basic concept of decomposition-coordination in a large-scale system theory, the *fuzzy model predictive controller* design can be accomplished through a *two-layer iterative design process*. The design is decomposed into the derivation of local controllers. The subsystems regulated by those local controllers will be coordinated to derive a *globally optimal control policy*.

One of the main objectives of the application is to supply *an integrated solution of systems, which should support all the phases of the life cycle: modeling, simulation, development and implementation*. For *parameter tuning, for validation and also for embedding a large number of industrial communication protocols, multi-disciplinary simulation environments are developed which generate instruments for control, I/O data consistency check, and defect detection*. In the end, *real-time advanced control applications* are developed, with *seamless* and *gradual integration into the existing distributed control system*.

In order to provide the real-time characteristic, we choose a multitasking environment for the application (WINDOWS Operating System). From structural point of view we propose a Client / Server architecture for fuzzy Controller (FC) [2]:

Client - is a Windows application representing the implementation of the graphical user interface (GUI). The Client enables the operator to control the system in two modes: manual/automatic, to monitor the system response, etc. The Client has also the ability to connect and communicate with the Server application.

Server is an ActiveX EXE application containing the implementation of the FC kernel. The Server includes a collection of objects, these objects cover the tasks of both data processing and the communication between dedicated applications for input and output data.

The Client application will have a thread pool architecture. The Server application will have a real multithreading architecture (each active object having assigned its own execution thread). The Server have also a multi-layer structure: at the higher level are implemented upper FC and the communication classes (using different transmission mechanisms DDE, OPC, HLI, ActiveX, Winsocket, Pipes), at the lower level are implemented the controllers for the subsystems corresponding to the low level FC. The Server's application as real multithreading architecture, provides the FC Kernel the real-time response characteristic, required for the industrial process control.

4 Conclusions

Control of SG water level strongly affects nuclear power plant availability. The control task is difficult for a number of reasons, the most important among them being the nonlinear plant dynamics and the non-minimum phase plant characteristics. There has been a special interest in this problem during low power transients because of the dominant reverse thermal dynamic effects known as shrink and swell.

The SG level control problem was viewed as a single input/single output control problem with the feed-water as the manipulated variable, the level as the controlled variable and the turbine steam demand as disturbance. The process non-linearity was addressed by scheduling the model (and the controller) with the power level. The SG system is modeled by Takagi-Sugeno's fuzzy modeling methodology, where the system output is estimated based on gradient. The complex shrink and swell phenomena associated with the SG water level are well captured by the model. The predictive controller based on fuzzy model is designed in a hierarchical control design.

An original concept of modular evolved control system, seamless and gradual integration into the existing distributed control system is proposed in the paper. A unified API of extended generality and extendibility in order to unify access and information retrieval from various wireless and wired technology and communication interfaces is developed in order to ensure independence between communication and control modules of the designed systems.A Client / Server architecture for evolved controller that runs on the Windows environment, with real-time characteristics is proposed.

Bibliography

[1] Akkurt, Colak U., PWR system simulation and parameter estimation with neural networks, *Annals of Nuclear Energy*, Vol. 29, pp. 2087-2103, 2002.

[2] Andone D. ,Dobrescu R., Hossu A., Dobrescu M., Application of fuzzy model predictive control to a drum boiler, *ICAE - Integrated Computer-Aided Engineering*, IOSPress, 13(4):347-361, 2006.

[3] Andone D., Hossu A., Predictive Control Based on Fuzzy Model for Steam Generator, *2004 IEEE International Conference on Fuzzy Systems, Proc. FUZZ-IEEE 2004*, vol. 3, IEEE Catalog Number 04CH37542, ISBN 0-7803-8353-2, ISNN 1098-7584, Budapest, Hungary; pp. 1245-1250; July 25-29, 2004.

[4] Andone D., Fagarasan I., Dobrescu M., Advanced Control of a Steam Generator, *The 3rd International IEEE Conference Intelligent Systems, September 04-06, 2006 3rd International IEEE Conference Intelligent Systems*, Vol.s 1 and 2, London, United Kingdom, pp. 338-343, 2006.

[5] Aström K., Bell R., Drum-boiler dynamics, *Automatica* 3, pp. 363-378, 2000.

[6] Camacho E., Bordons C., *Model Predictive Control*, Springer-Verlag, London, 2004.

[7] Demircioglu H., Karasu E., Generalized Predictive Control - A Practical Application and Comparation of Discrete and Continuous-Time Versions, *IEEE Control Systems*, Oct 2000, 20(5):36-44, 2000.

[8] Dubois D., Prade H., *Fuzzy Sets and Systems: Theory and Applications*, Academic Press, Inc., Orlando, FL, 1997.

[9] Espinosa J., Hadjili M. L., Wertz V.,and Vanderwalle J., Predictive control using fuzzy models. Comparative study, *European Control Conference*, Karlsruhe, Germany, Sept. 1999.

[10] Huang Y., Lou Helen H., Gong J.P., Edgar Th. F., Fuzzy Model Predictive Control, *IEEE Trans. On Fuzzy Systems*, 8(6):665-668, 2000.

[11] Hirota K., *Industrial Applications of Fuzzy Technology*, Springer-Verlag, New York, 1993

[12] Irving E., Miossec C., and Tassart J., Toward efficient full automatic operation of the PWR steam generator with water level adaptive control, *Proc. Int. Conf. Boiler Dynamics Contr. Nuclear Power Stations*, London, U.K., pp. 309-329, 1980.

[13] Kiriakidis K., Non-linear control system design via fuzzy modeling and LMIs, *International Journal of Control*, 72(7):676-685, 1999.

[14] Kothare M., Mettler B., Morari M., Bendotti P., Falinower C., Level Control in the Steam Generator of a Nuclear Power Plant, *IEEE Trans. On Control Systems Technology*, 8(1):55-69, 2000.

[15] Menon S.K. and Parlos A.G., *Gain-scheduled nonlinear control of U-tube steam generator water level*, Nuclear Sci. Eng., vol. 111, pp. 294-308, 1992.

[16] Morari M. and Lee J. H., Model predictive control: Past, present, and future, *Computers & Chemical Eng.*, pp. 667-682, 1999.

[17] Park G. Y., Seong P. H., Application of a self-organizing fuzzy logic controller to nuclear steam generator level control, *Nuclear Engineering and Design*, vol. 167, pp. 345-356, 1997.

[18] Pedrycz W. and Gomide, F., *Fuzzy Systems Engineering: Toward Human-Centric Computing*, Wiley-IEEE Press, 2007.

[19] Precup, R. E., Tomescu M., Preitl S., Lorenz System Stabilization Using Fuzzy Controllers, *International Journal of Computers Communications and Control*, 2(3):279-287, 2007.

[20] Ross T.J., *Fuzzy Logic with Engineering Applications*, second ed., Wiley & Sons, 2004.

[21] Vesselenyi, T; Dzitac, S; Dzitac, I, Manolescu M.J., Fuzzy and neural controllers for a pneumatic actuator, *International Journal Of Computers Communications & Control*, 2(4):375-387, 2007.

[22] Yager R., R., Zadeh L. A., *An Introduction to Fuzzy Logic Applications in Intelligent Systems*, Kluwer Academic Publishers, Norwell, MA, 1992.

[23] Yen J., Langari R., Zadeh L., A., *Industrial Applications of Fuzzy Logic and Intelligent Systems*, IEEE Press, Piscataway, NJ, 1995.

[24] Ying H., *Fuzzy Control and Modeling: Analytical Foundations and Applications*, Wiley-IEEE Press, 2000.

[25] Zadeh, L. , A New Frontier in Computation - Computation with Information Described in Natural Language, *International Journal of Computers Communications and Control*, 3(S):26-27, 2008.

[26] Zadeh L. A., Toward a generalized theory of uncertainty (GTU): an outline, *Information Sciences-Informatics and Computer Science: An International Journal*, 172(1-2):1-40, 2005.

[27] Zadeh, L. A., Knowledge Representation in Fuzzy Logic, *IEEE Transactions on Knowledge and Data Engineering*, 1(1):89-100, 1989.

[28] Zadeh, L. A., Is there a need for fuzzy logic?, *Information Sciences: an International Journal*, 178(13):2751-2779, 2008.

[29] Zadeh L.A., Tufis D., Filip F.G., Dzitac I.(Eds.), *From Natural Language to Soft Computing: New Paradigms in Artificial Intelligence*, Editing House of Romanian Academy, Bucharest, ISBN 978-973-27-1678-6, 2008.

[30] Zhao F., Ou J., Du W., Simulation modeling of nuclear steam generator water level process a case study, *ISA Transactions*, 39, pp. 143-151, 2000.

Daniela Hossu is Associated Professor at University "Politehnica" of Bucharest. In 1996 she obtained M.S. degree in Electrical Engineering, Specialty - Control Systems and Informatics in Power Systems at University "Politehnica" of Bucharest. In 2002 she obtained a Ph.D. in Automatic Control from the University "Politehnica" of Bucharest. She was involved in several projects for retrofitting the Instrumentation & Control System of Thermal Power Plants. Since 1998 she has been involved in lecturing and teaching assistantships at University "Politehnica" of Bucharest in the following fields: automatic control, data transmission and data compression. Her research interests include Power Plant Control Systems, Artificial Intelligence, Industrial Communication, Data Compression, Software architectures for industrial control.

Ioana Făgărăşan received the M.S. (1996) degree in Electrical Engineering, Specialty - Control systems and Informatics in Power Systems, and the PhD (2002) degree in Automatic Control from the University Politehnica of Bucharest (UPB). Since 1996 she has been Assistant Professor, Lecturer and is currently Associated Professor in the department of Control Engineering and Industrial Informatics at the UPB. She has participated in research cooperation programs between the University and the Institute for Automatic Control, Technical University of Darmstadt, in the Fault Detection and Identification (FDI) field. Between 2002 and 2004 she worked as associate professor at the National Polytechnic Institute of Grenoble (Automatic Control Laboratory). Her research interests include control system for technical processes, fault detection and isolation methods, diagnostic algorithms and fault tolerant systems.

Andrei Hossu is Professor at University "Politehnica" of Bucharest. In 1982 he obtained M.S. in Electrical and Computer Engineering, Department of Automatic Control and Computers, The Polytechnic Institute of Bucharest, Romania. In 2002 he obtained a Ph.D. in Engineering Sciences, the Electrical control field from the Faculty of Automatic Control and Computers, the University "Politehnica" of Bucharest, Romania. His teaching interests include: Human-Machine Interface, Artificial Vision and Artificial Intelligence Methods. His research interests include: Multiprocessor systems for real time control, Industrial robots control systems, Algorithms, methods for artificial vision systems for industrial robots, Structured programming for industrial robots, Software architectures for industrial control.

Sergiu Stelian Iliescu has received the M.S. (1965) degree from the Power System Faculty, Automatic Control Department and Ph. D. (1979) degree in Computers- Electronics from University "Politehnica" of Bucharest (UPB). He was starting his professional activity in execution and implementation of automatic control equipments and systems, within the Automatic Control System Execution Company (IMIA). The next step was to work as design engineer within Power Systems Studies and Design Institute (ISPE). Since 1968 he is part of the teaching and research team from Automatic Control and Computers Faculty, UPB and acts as Full Professor since 1995. He has experience in process computers (TU Dresden, 1971-1972) and coordinates collaborative research activities with TU Darmstadt (1992-2004), in two research field: in system theory, modeling, identification and control technical processes (Institute of Automatic Technique, TUD) and in power system control and monitoring (Institute of Electrical Power Systems, TUD). His research and teaching domain includes: automatic control theory, informatics system for supervision and control of industrial processes with concern to power system field and system engineering analysis.