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Fuzzy Model Level Predictive Control for a Drum Boiler

Daniela Andone[*]

[*]University "POLITEHNICA" of Bucharest, Faculty of Control and Computers
Splaiul Independentei nr.313, Bucuresti - 77206, ROMANIA
Tel. +401 410 0400/105; E-mail: dana@aii.pub.ro

Abstract: Economic feasibility of a power plant requires smooth and uninterrupted plant operation in the face of varying electrical power demand. The feed-water system in a power plant is a major contributor to plant unavailability. In this paper, a fuzzy model predictive control (FMPC) approach is introduced to design a level control system in a drum boiler. In this approach, the process is described by a fuzzy convolution model that consists of a number of quasi-linear fuzzy implications (FI). The whole process behavior is characterized by a weighted sum of the outputs from all quasi-linear fuzzy implications. In controller design, prediction errors and control energy are minimized through a two-layered iterative optimization process. At the lower layer, optimal local control policies are identified to minimize prediction errors in each subsystem. A near optimum is then identified through coordinating the subsystems to reach an overall minimum prediction error at the upper layer. A client/server architecture is proposed for implementation.
Keywords – drum boiler, level control, nonlinear system, fuzzy logic, model predictive control.

1. Introduction

The difficulties in designing an effective level control system in a drum boiler arise from a number of factors:

- *Nonlinear plant characteristics*. The plant dynamics are highly nonlinear. This is reflected by the fact that the linearized plant model shows significant variation with operating power.
- *Non-minimum-phase plant characteristics*. The plant exhibits strong inverse response behavior, particularly at low operating power due to the so-called "*swell and shrink*" effects.
- *Constraints*. The feed-water system can only deliver a limited throughput of water to the drum. This imposes a hard limitation on the available control action.

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; LQG controllers with "gain-scheduling" to cover the entire operating range; a hybrid fuzzy-PI adaptive control of steam generator, 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.

With the advent of the current generation of high-speed computers, more advanced control strategies not limited to PI/PID, can be applied. MPC is one such controller design technique, which has gained wide acceptance in process control applications in the chemical industries. Model predictive control has three basic steps [3]: output prediction, control calculation and closing the feedback loop. In this paper, we apply MPC techniques to develop a framework for systematically addressing the various issues in the drum level control problem. A new fuzzy logic-based modeling methodology, where a nonlinear system is divided into a number of linear or nearly linear subsystems is introduced, where a fuzzy quasi-linear model based on Takagi-Sugeno's modeling methodology is developed for each subsystem [5]. The whole process behavior is characterized by a weighted sum of the outputs from quasi-linear models. The paper includes simulations of typical operating transients in the drum and an implementation in a client/server architecture.

2. Plant Description

The main steam generator types decisively influences the control schemes to be applied. The most widespread drum boiler is the natural circulation boiler. Here the feedwater pump forces the water through the economizer into the drum. From there it is supplied to the lower furnace wall headers through a system of mostly unheated downcomer tubes. Steam is generated as the water rises through the furnace wall riser tubes exposed to heat radiation. The water/steam mixture is then transferred to the boiler drum. The circulation is maintained by the difference in the densities in the downcomers and in the risers. Steam is separated from the steam/water mixture in the drum, and leaves the boiler through the superheater section [2]. Figure 1 shows the system under consideration. It consists of an economiser, a drum, and an evaporation/circulation system.

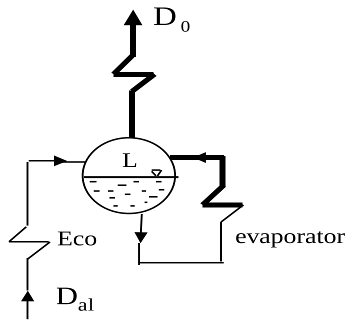

Fig. 1 – Plant scheme of a level controlled system in a drum boiler.

The individual symbols have the following meanings: D_{al} - feedwater flow into economizer, D_0 - steam flow out of drum, L - level in the drum. The main problem in setting up a signal flow diagram for a level controlled system in a drum boiler can be found in the inhomogeneous contents of the evaporator and the drum. 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 course, means that the steam content also strongly influences the level in the drum. The steam content itself depends, in turn, on the load factor of the boiler, on the changes in feedwater flow, and on feedwater temperature. This is the reason for the “s*well and shrink”* phenomenon that in spite of an increased supply of water, the water level initially falls. The transient behavior of the water level in the drum is dominated by the thermodynamic properties of the two-phase mixture present in the drum and exhibits an inverse response behavior. Figure 2 shows responses of the water level to steps in feedwater and steam flow-rates at different operating powers [4].

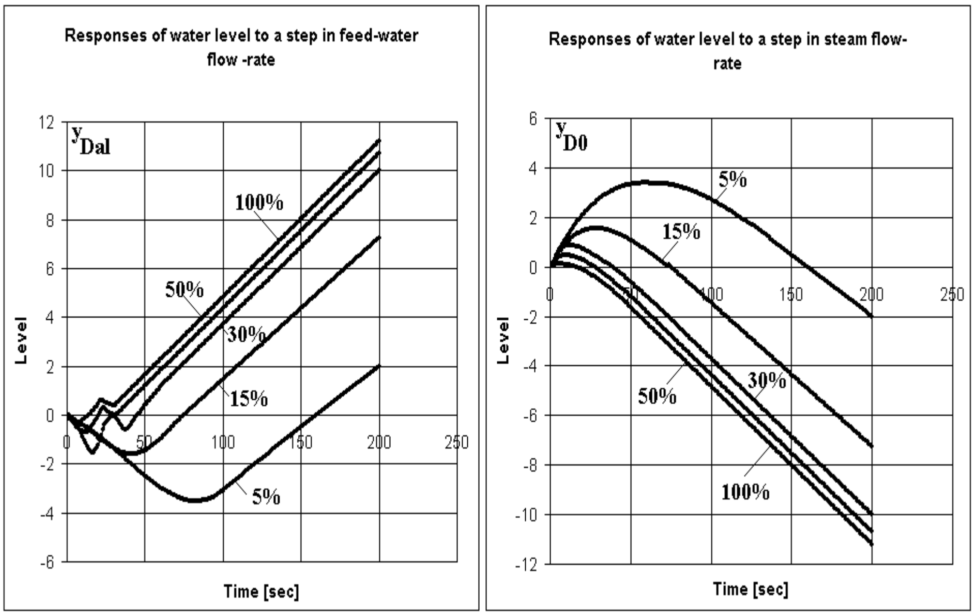

Fig. 2 – Responses of water level at different operating power (indicated by %) to (a) a step in feed-water flow –rate; (b) a step in steam flow-rate

The inverse response behavior of the water level is most severe at low power (5%). 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.

3. Fuzzy Model

Consider the response of water level at 5% operating power because of the strong inverse response. The system is decomposed into p=4 subsystems such that each subsystem demonstrates a linear or nearly linear behavior. 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* [1].

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

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

$\Delta u(n)$ 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.

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

where ω^j is the truth value for the jth fuzzy implication; it can be calculated based on the fuzzy sets in the IF part:

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

Consider a step in feed-water flow rate at 5% operating power:

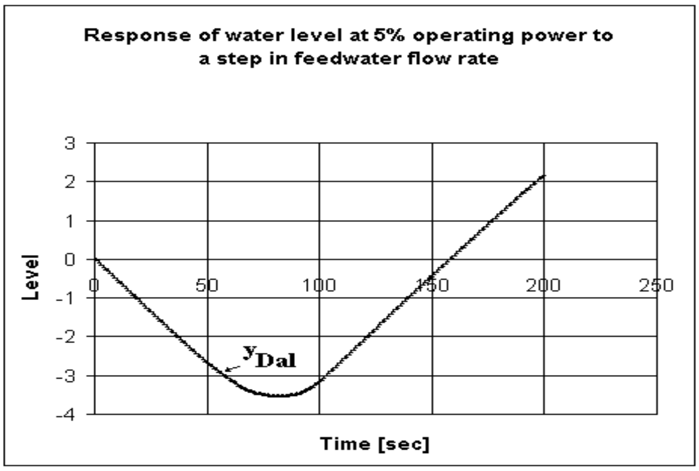

Fig. 3 – Response of water level at 5% operating power to a step in feed-water flow –rate

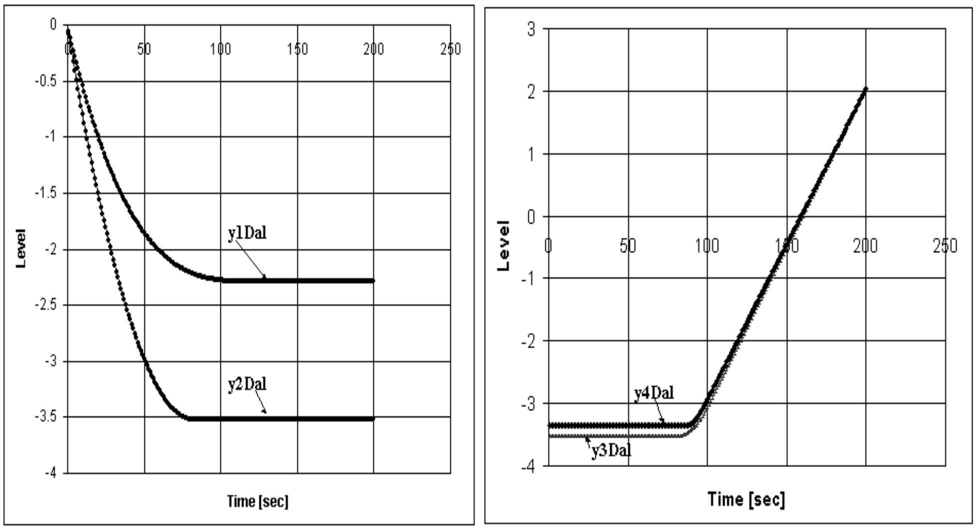

Fig. 4 – The system is decomposed into 4 subsystems: $y^1_{D_{al}}$, $y^2_{D_{al}}$, $y^3_{D_{al}}$, $y^4_{D_{al}}$

For this system, a fuzzy convolution model consisting of four FIs is developed as follows:

$$R^1 : IF\ y_{D_{al}}(n)\, is\ A^1$$
$$THEN\ y^1_{D_{al}}(n+1) = y^1_{D_{al}}(n) + \sum_{i=1}^{200} h\_D_{al}{}^1_i u(n+1-i) \tag{4}$$

	h1_Dal	h2_Dal	h3_Dal	h4_Dal
1	-0.058	-0.08	0	0
2	-0.057	-0.08	0.003	0.005
3	-0.056	-0.08	0.005	0.01
4	-0.055	-0.08	0.008	0.015
5	-0.054	-0.08	0.011	0.02
6	-0.053	-0.08	0.013	0.025
7	-0.052	-0.08	0.016	0.03
8	-0.051	-0.08	0.019	0.035
9	-0.05	-0.08	0.021	0.04
10	-0.049	-0.07	0.024	0.045
11	-0.048	-0.07	0.027	0.05
12	-0.047	-0.07	0.03	0.05
13	-0.046	-0.07	0.032	0.05
14	-0.045	-0.07	0.035	0.05
15	-0.044	-0.07	0.038	0.05
16	-0.043	-0.07	0.04	0.05
17	-0.042	-0.07	0.043	0.05
18	-0.042	-0.07	0.046	0.05
19	-0.041	-0.07	0.048	0.05
20	-0.04	-0.06	0.051	0.05
21	-0.039	-0.06	0.051	0.05
22	-0.038	-0.06	0.051	0.05
23	-0.037	-0.06	0.051	0.05
24	-0.036	-0.06	0.051	0.05
25	-0.036	-0.06	0.051	0.05
26	-0.035	-0.06	0.051	0.05

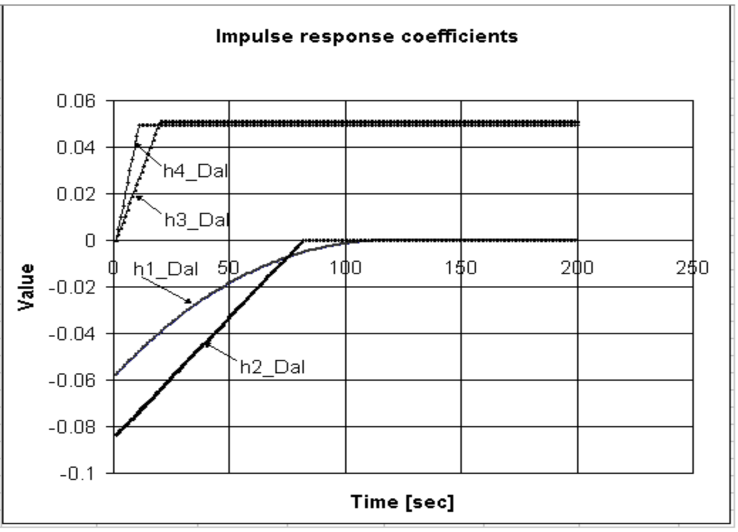

Fig. 5 – The impulse response coefficients for $y^1_{D_{al}}$, $y^2_{D_{al}}$, $y^3_{D_{al}}$, $y^4_{D_{al}}$ subsystem*s*

$$
\begin{aligned}
&R^2 : IF\ y_{D_{al}}(n)\, is\ A^2 \\
&\quad THEN\ y^2_{D_{al}}(n+1) = y^2_{D_{al}}(n) + \sum_{i=1}^{200} h\_D_{al}{}^2_i u(n+1-i)
\end{aligned}
\tag{5}
$$

$$
\begin{aligned}
&R^3 : IF\ y_{D_{al}}(n)\, is\ A^3 \\
&\quad THEN\ y^3_{D_{al}}(n+1) = y^3_{D_{al}}(n) + \sum_{i=1}^{200} h\_D_{al}{}^3_i u(n+1-i)
\end{aligned}
\tag{6}
$$

$$
\begin{aligned}
&R^4 : IF\ y_{D_{al}}(n)\, is\ A^4 \\
&\quad THEN\ y^4_{D_{al}}(n+1) = y^4_{D_{al}}(n) + \sum_{i=1}^{200} h\_D_{al}{}^4_i u(n+1-i)
\end{aligned}
\tag{7}
$$

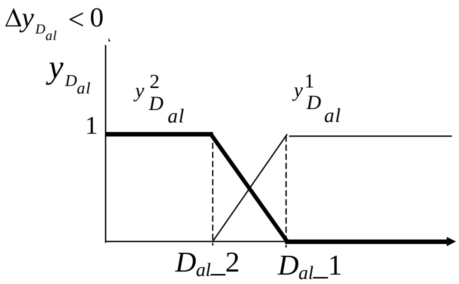

Fig. 6 - Definition of fuzzy sets A^1 and A^2 for FIs R^1 and R^2 respectively

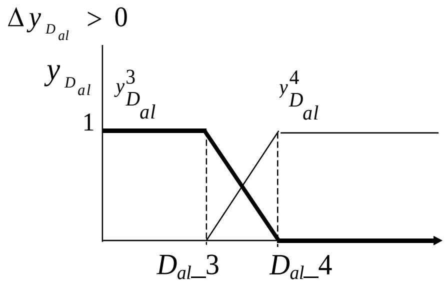

Fig. 7 - Definition of fuzzy sets A^3 and A^2 for FIs R^3 and R^4 respectively

In order to define the fuzzy sets we propose the following strategy:

$$D_{al}\_1=\min\left(y^1_{D_{al}}\right)\cdot K\_D_{al}\_1,\; D_{al}\_2=\min\left(y^2_{D_{al}}\right)\cdot K\_D_{al}\_2,$$

$$D_{al}\_3=\min\left(y^3_{D_{al}}\right)\cdot K\_D_{al}\_3,\; D_{al}\_4=\min\left(y^4_{D_{al}}\right)\cdot K\_D_{al}\_4 \text{ where}$$

$$K\_D_{al}\_1=0.2,\; K\_D_{al}\_2=0.9,\; K\_D_{al}\_3=0.9,\; K\_D_{al}\_4=0.2$$

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. Consider a step in steam flow rate at 5% operating power:

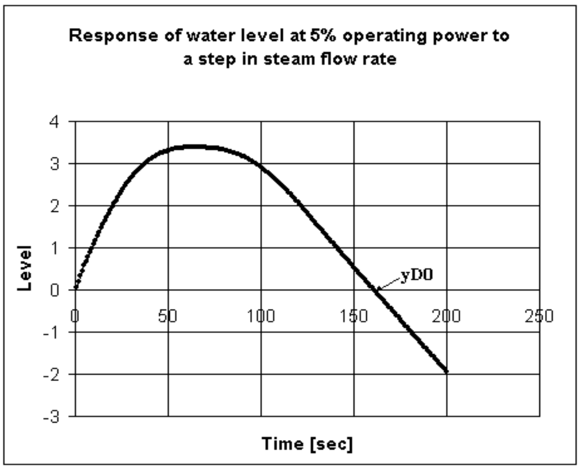

Fig. 8 – Response of water level at 5% operating power to a step in steam flow –rate;

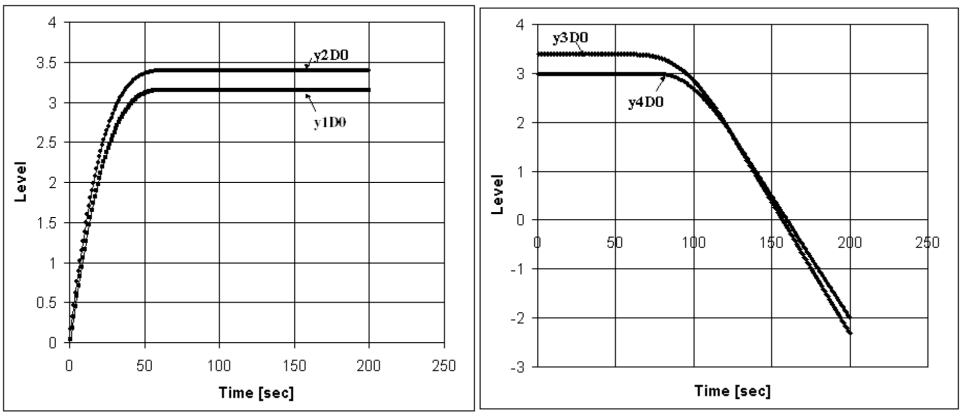

Fig. 9 – The system is decomposed into 4 subsystems: $y^1_{D_0}$, $y^2_{D_0}$, $y^3_{D_0}$, $y^4_{D_0}$.

	h1_D0	h2_D0	h3_D0	h4_D0
1				
2	0.14	0.156	0	0
3	0.14	0.151	-0	-0
4	0.13	0.146	-0	-0
5	0.13	0.141	-0	-0
6	0.12	0.136	-0	-0
7	0.12	0.131	-0	-0.01
8	0.12	0.126	-0	-0.01
9	0.11	0.121	-0	-0.01
10	0.11	0.116	-0	-0.01
11	0.1	0.112	-0	-0.01
12	0.1	0.108	-0	-0.01
13	0.1	0.103	-0	-0.01
14	0.09	0.099	-0	-0.02
15	0.09	0.095	-0.01	-0.02
16	0.09	0.091	-0.01	-0.02
17	0.08	0.087	-0.01	-0.02
18	0.08	0.083	-0.01	-0.02
19	0.08	0.08	-0.01	-0.02
20	0.07	0.076	-0.01	-0.02
21	0.07	0.072	-0.01	-0.02
22	0.07	0.069	-0.01	-0.03
23	0.06	0.066	-0.01	-0.03
24	0.06	0.062	-0.01	-0.03
25	0.06	0.059	-0.01	-0.03
26	0.06	0.056	-0.01	-0.03

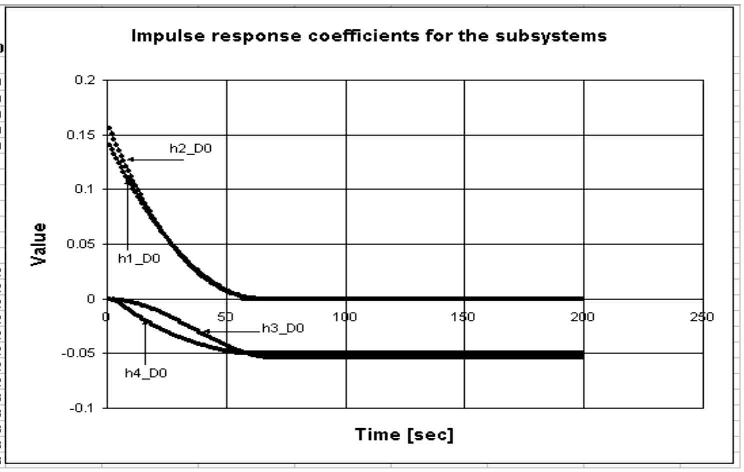

Fig. 10 – The impulse response coefficients for $y^1_{D_0}$, $y^2_{D_0}$, $y^3_{D_0}$, $y^4_{D_0}$ subsystems

For this system, a fuzzy convolution model consisting of four FIs is developed as follows:

$$R^1 : IF\ y_{D_0}(n)\ is\ A^1 \quad THEN\ y^1_{D_0}(n+1) = y^1_{D_0}(n) + \sum_{i=1}^{200} h\_D_{0i}^1 u(n+1-i) \tag{8}$$

$$R^2 : IF\ y_{D_0}(n)\ is\ A^2 \quad THEN\ y^2_{D_0}(n+1) = y^2_{D_0}(n) + \sum_{i=1}^{200} h\_D_{0i}^2 u(n+1-i) \tag{9}$$

$$R^3 : IF\ y_{D_0}(n)\ is\ A^3 \quad THEN\ y^3_{D_0}(n+1) = y^3_{D_0}(n) + \sum_{i=1}^{200} h\_D_{0i}^3 u(n+1-i) \tag{10}$$

$$R^4 : IFA\, y_{D_0}(n)\ is\ A^4 \quad THEN\ y^4_{D_0}(n+1) = y^4_{D_0}(n) + \sum_{i=1}^{200} h\_D_{0i}^4 u(n+1-i) \tag{11}$$

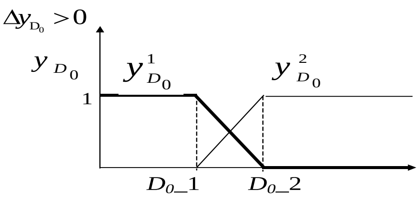

Fig. 11 – Definition of fuzzy sets A^1 and A^2 for FIs R^1 and R^2 respectively

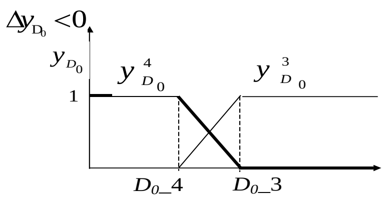

Fig. 12 – Definition of fuzzy sets A^3 and A^2 for FIs R^3 and R^4 respectively

In order to define the fuzzy sets we propose the following strategy:

D0_1=max($y_{D_0}^1$)*K_D0_1, D0_2=max($y_{D_0}^2$)*K_D0_2, D0_3=max($y_{D_0}^3$)*K_D0_3, D0_4=max($y_{D_0}^4$)*K_D0l_4; where K_D0_1=0.4, K_D0_2=0.9, K_D0_3=0.9, *K_D0*_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.

4. Fuzzy Model Predictive Control

4.1. Problem formulation

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

$$\min_{\Delta u(n),\, \Delta u(n+1,\ldots,\Delta u(n+N_u))} J(n) \tag{12}$$

$$J(n) = \sum_{i=1}^{N_y} \mu_i \,(\hat{y}(n+i) - y^r(n+i))^2 + \sum_{i=1}^{N_u} \upsilon_i \Delta u(n+i)^2 \tag{13}$$

where:

μ_i and υ_i are the weighting factors for the prediction error and control energy;

$\hat{y}(n+i)$ *i*-th step output prediction;

$y^r(n+i)$ *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:

$$\Delta u(n+i) = \sum_{j=1}^{p} \omega^j \Delta u^j(n+i) \tag{14}$$

Substituting (2) and (14) into (13) yields

$$J(n) = \sum_{i=1}^{N_y} \mu_i \left(\sum_{j=1}^{p} \left(\omega^j \left(\hat{y}^j(n+i) - y^r(n+i)\right)\right)\right)^2 + \sum_{i=0}^{N_u-1} \nu_i \left(\sum_{j=1}^{p} \omega^j \Delta u^j(n+i)\right)^2 \tag{15}$$

To simplify the computation, an alternative objective function is proposed as a satisfactory approximation of (15) [4]. According to the Cauchy inequality:

$$\left(\sum_{j=1}^{p}\omega^{j}\left(\hat{y}^{j}(n+i)-y^{r}(n+i)\right)\right)^{2}\leq p\sum_{j=1}^{p}\left(\omega^{j}\left(\hat{y}^{j}(n+i)-y^{r}(n+i)\right)\right)^{2} \tag{16}$$

$$\left(\sum_{j=1}^{p}\omega^{j}\Delta u^{j}(n+i)\right)^{2}\leq p\sum_{j=1}^{p}\left(\omega^{j}\Delta u^{j}(n+i)\right)^{2} \tag{17}$$

This allows us to define the following alternative objective function:

$$\tilde{J}(n)=\sum_{j=1}^{p}\left(\left(\omega^{j}\right)^{2}\left(\sum_{i=1}^{N_y}\mu_i\left(\hat{y}(n+i)-y^{r}(n+i)\right)^{2}+\sum_{i=0}^{N_u-1}\nu_i\Delta u^{j}(n+i)^{2}\right)\right) \tag{18}$$

The optimization problem can be defined as:

$$\min_{\Delta u(n),\Delta u(n+1),\ldots,\Delta u(n+N_u-1)}\tilde{J}(n)=\min_{\Delta u(n),\Delta u(n+1),\ldots,\Delta u(n+N_u-1)}\sum_{j=1}^{p}\left(\omega^{j}\right)^{2}\tilde{J}^{j}(n) \tag{19}$$

where

$$\tilde{J}^{j}(n)=\sum_{i=1}^{N_y}\mu_i\left(\hat{y}^{j}(n+i)-y^{r}(n+i)\right)^{2}+\sum_{i=0}^{N_u-1}\nu_i\left(\Delta u^{j}(n+i)\right)^{2} \tag{20}$$

Using the alternative objective function (20), we can derive 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 (20) can be rewritten in a matrix form as follows:

$$\tilde{J}^{j}(n)=\left(\hat{\mathrm{Y}}_{+}^{j}(n)-\mathrm{Y}^{r}(n)\right)^{T}\mathrm{W}_{1}^{j}\left(\hat{\mathrm{Y}}_{+}^{j}(n)-\mathrm{Y}^{r}(n)\right)+\left(\Delta\mathrm{U}_{+}^{j}(n)\right)^{T}\mathrm{W}_{2}^{j}\left(\Delta\mathrm{U}_{+}^{j}(n)\right) \tag{21}$$

where:

$$\hat{\mathrm{Y}}_{+}^{j}(n)=\left(\hat{y}_{D_{al}}{}^{j}(n+1)\;\hat{y}_{D_{al}}{}^{j}(n+2)\cdots\hat{y}_{D_{al}}{}^{j}(n+N_y)\right)^{T} \tag{22}$$

$$\mathrm{Y}^{r}(n)=\left(y^{r}(n+1)\;y^{r}(n+2)\cdots y^{r}(n+N_y)\right)^{T} \tag{23}$$

$$\Delta\mathrm{U}_{+}^{j}(n)=\left(\Delta u^{j}(n)\;\Delta u^{j}(n+1)\cdots\Delta u^{j}(n+N_u-1)\right)^{T} \tag{24}$$

$$\mathrm{W}_{1}^{j}=diag\left\{\mu_1^{j},\mu_2^{j},\cdots,\mu_{N_y}^{j}\right\} \tag{25}$$

$$\mathrm{W}_{2}^{j}=diag\left\{\nu_1^{j},\nu_2^{j},\cdots,\nu_{N_u}^{j}\right\} \tag{26}$$

The N_y – step prediction of the output by the *j*-th FI can be rewritten as follows:

$$\mathrm{A}^j = \begin{bmatrix} a_1^j & 0 & 0 & \cdots & 0 \\ a_2^j & a_1^j & 0 & & 0 \\ a_3^j & a_2^j & a_1^j & & 0 \\ \vdots & & & & \vdots \\ a_{N_y}^j & a_{N_y-1}^j & a_{N_y-2}^j & \cdots & a_{N_y-N_u+1}^j \end{bmatrix} \tag{28}$$

$$a_i^j = \sum_{k=1}^{i} h_k^j \tag{29}$$

$$\mathrm{Y}(n) = \left(y_{D_{al}}(n)\, y_{D_{al}}(n) \cdots y(n)_{D_{al}}\right)^T \tag{30}$$

$$\mathrm{P}^j(n) = \left(P_1^j(n)\, P_2^j(n) \cdots P_{N_y}^j(n)\right)^T \tag{31}$$

$$\mathrm{E}_+^j(n) = \left(0\ \sum_{k=1}^{2} \varepsilon^j(n+k-1) \cdots \sum_{k=1}^{N_y} \varepsilon^j(n+k-1)\right)^T \tag{32}$$

$$P_i^j(n) = \sum_{k=1}^{i} \sum_{l=k+1}^{T} h_l^j \Delta u(n+k-l) \tag{33}$$

The resulting control policy for the *j*-th subsystem can be derived as

$$\begin{aligned} \tilde{\mathrm{J}}^j(n) = {} & \left(\Delta \mathrm{U}_+^j(n)\right)^T \left(\mathrm{A}^{j^T} \mathrm{W}_1^j \mathrm{A} + \mathrm{W}_2^j\right) \Delta \mathrm{U}_+^j(n) + \left(\Delta \mathrm{U}_+^j(n)\right)^T \mathrm{A}^{j^T} \mathrm{W}_1^j \mathrm{Z}^j(n) + \\ & + \left(\mathrm{Z}^j(n)\right)^T \mathrm{W}_1^j \mathrm{A}^j \Delta \mathrm{U}_+^j(n) + \left(\mathrm{Z}^j(n)\right)^T \mathrm{W}_1^j \mathrm{Z}^j(n) \end{aligned} \tag{34}$$

where:

$$\mathrm{Z}^j(n) = \mathrm{Y}(n) - \mathrm{Y}^r(n) + \mathrm{P}^j(n) + \mathrm{E}_+^j(n) \tag{35}$$

Minimizing (6.46) yields

$$\frac{\delta \tilde{J}^j(n)}{\delta \Delta \mathrm{U}_+^j(n)} = 2\left(\mathrm{A}^{j^T} \mathrm{W}_1^j \mathrm{A}^j + \mathrm{W}_2^j\right) \Delta \mathrm{U}_+^j(n) + 2\,\mathrm{A}^{j^T} \mathrm{W}_1^j \mathrm{Z}^j(n) = 0 \tag{36}$$

The control law by the *j*-th FI can be identified as

$$\left(\Delta \mathrm{U}_+^j(n)\right)^* = -\mathrm{K}^j \mathrm{Z}^j(n) \tag{37}$$

where K^j is:

$$\mathrm{K}^{j} = \left(\mathrm{A}^{j^T}\,\mathrm{W}_1^j\,\mathrm{A}^{j} + \mathrm{W}_2^j\right)^{-1} \mathrm{A}^{j^T}\,\mathrm{W}_1^j \tag{38}$$

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.

$$\Delta\,\mathrm{U}_{+}(n) = \left(\Delta u(n)\;\Delta u(n+1)\cdots\Delta u(n+N_u-1)\right)^T \tag{39}$$

4.2. FMPC design/simulation system

Underlying the basic objective of FMPC design/simulation system, there are three different issues, which have individual motivation:

High degree user interactivity (especially during the design process).

High mathematical processing power.

Mathematical processing tasks automation.

According to these issues a Client /Server architecture is proposed:

Server (mathematical): MATLAB; Client: EXCEL with VBA (Visual Basic for Applications) modules for mathematical processing tasks automation and DDE link with MATLAB.

4.3. 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. So far, there has no rigorous solution to the selection of optimal model horizon (T), control horizon (N_u) and prediction horizon (N_y). The model horizon is selected so that $T\Delta t \geq$ open-loop settling time. 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.

The ranges of weighting factors W_1^j and W_2^j can be very wide, the importance their relative magnitudes.

The following three-step procedure to tune the weighting factors is proposed:

Step 1) Select a value for W_1 and assign it to all 4 local controllers. Determine W_2^j independently for each local controller in order to minimize the objective function for that subsystem

Step 2) Identify the largest W_2 and assign it to all subsystems.

Step 3) 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.

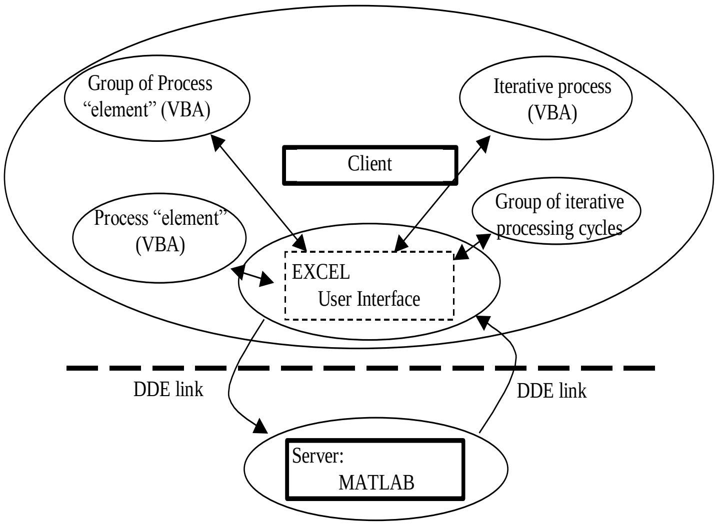

Fig. 13 – Structure of FMPC design/simulation system

SIMULATIONS

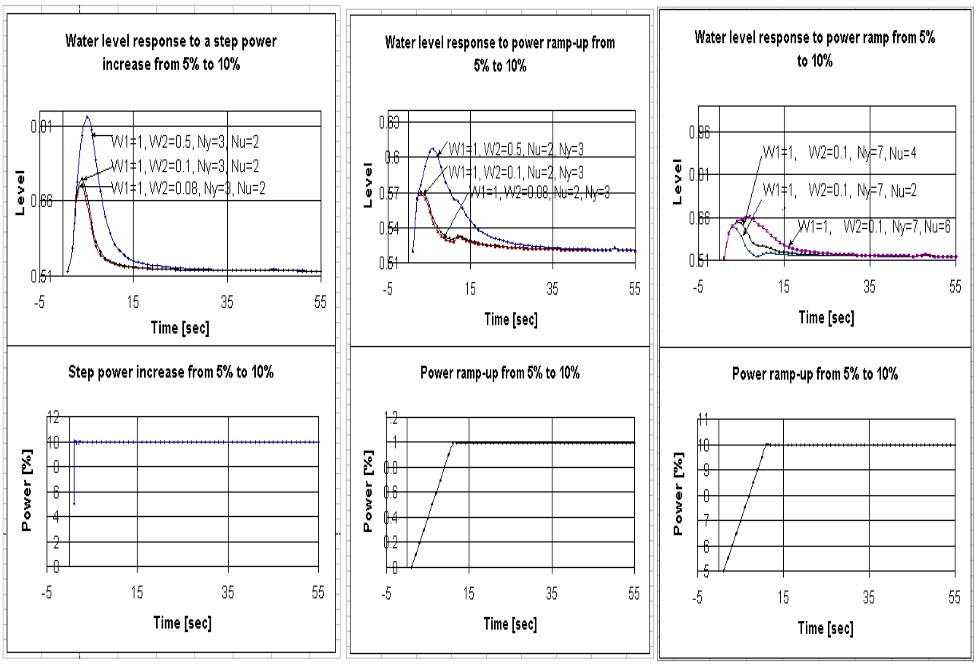

Fig. 14 – Water level response to a) step power increase from 5% to 10% (Nu=2, Ny=3) b) to power ramp up from 5% to 10% (Nu=2, Ny=3) c) to power ramp up from 5% to 10% (Ny=7, Nu=2, Nu=4, Nu=6)

5. Fuzzy MPC Client/Server Architecture

A client/server architecture for fuzzy MPC is proposed:

Client - is an EXE Windows application, which is responsible with GUI (graphical user interface – enable the operator to control the system in two modes: manual/automatic, to monitor the system response, etc)

Server – is an ActiveX EXE application contains a collection of objects (this modules are responsible with communication via applications (DDE support) dedicated for input/output data, processing data – which is the kernel FMPC) .

The Client application has a Tread Pool architecture. The Server application is a multi-layer, multithreading (because of ActiveX – EXE structure which enable Tread per Object) application. At the higher level there are implemented upper FMPC and the two communication classes (input/output DDE channels), at the lower level there are implemented the controllers for the *p* subsystems corresponding to the low level FMPC.

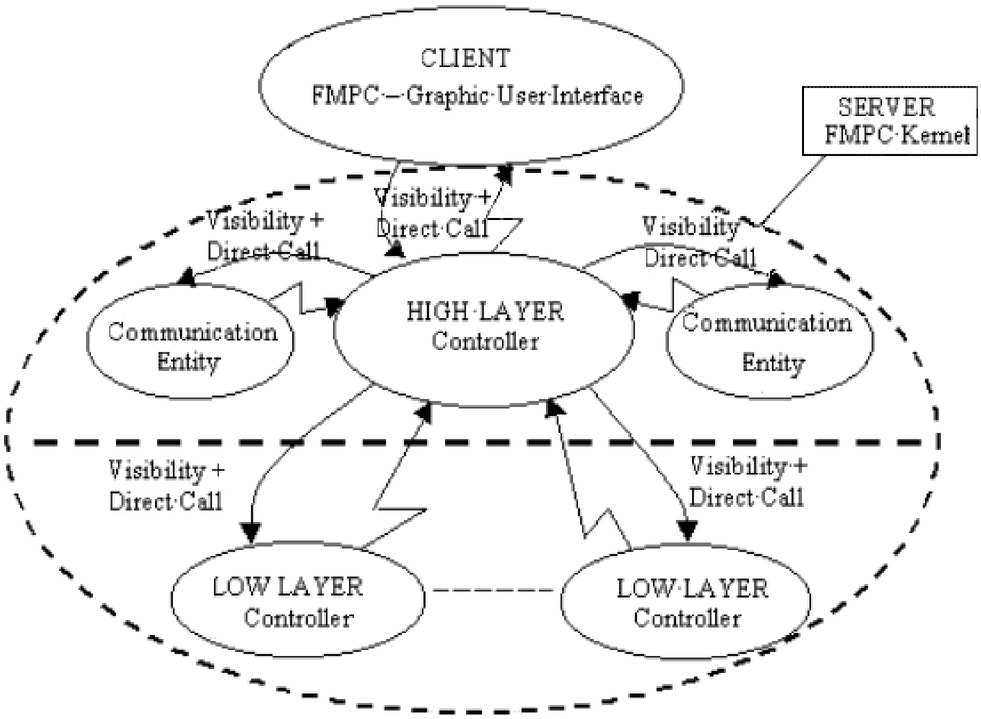

Fig. 15 – FMPC Client /Server architecture

6. Conclusions

The drum level control problem was viewed as a single input/single output (SISO) control problem with the feedwater as the manipulated variable, the level as the controlled variable and the turbine steam demand as disturbance. 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. The process nonlinearity was addressed by scheduling the model (and the controller) with the power level. The drum (steam generator) system is modeled by Takagi-Sugeno's fuzzy modeling methodology, where the system output is estimated based on gradient. The controller is designed in a hierarchical control design. A client/server architecture for design/simulation system is proposed. A client/server FMPC architecture for on-line implementation is proposed. The Server application is a multi-layer application. At the higher level there are implemented upper FMPC and the two communication classes (input/output DDE channels), at the lower level there are implemented the controllers for the *p* subsystems corresponding to the low-level FMPC.

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