MODELING AND SIMULATION OF THE DYNAMICS OF HYDRO-ENERGETIC SYSTEMS

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Abstract: This paper presents a strategy for modeling and simulation of the hydro-energetic dam dynamics. The useful information for the evaluation of the mathematical models is represented by a data set collected for twenty years from one of the hydro-energetic systems in Romania. The results of our work allow the evaluation of the present state of this system and offer some important information for the computer aided design of similar systems. These results have been obtained using software tools dedicated to data acquisition, modeling, identification and simulation.

Keywords: hydro-energetic dam, multivariable system, data measurement, modeling identification, simulation.

Presenting Author's Biography:

Silviu Cirstoiu. Silviu Cirstoiu is a Politehnica University of Bucharest 2008 Automation Graduate who continued his studies through a Systems Engineering Masters Program. His is currently improving his studies and research through a PhD doctoral program at Politehnica University of Bucharest in collaboration with Universite Picardie d'Amiens, France. His is undergoing a research stage in Amiens modeling and controlling the behavior of the modern turbo charged diesel engine. The goal is to limit even more the NO2 exhaust gases of the engine through studies made over the relationships between pressures and torques inside the engine.

1. INTRODUCTION

Two procedures of evaluating the mathematical models of the dynamics of a hydro-energetic dam have been proposed. These procedures were used in order to study the hydro-energetic systems in Romania (Tarnita dam) and they consist of:

1) A global evaluation of a non-linear multivariable stationary model for slows variations in the evolution of the whole observation interval (data measurement between 1989 and 2009). The solution of this problem was given by the off-line identification Least-Squares method (LS). The structure of the global model, which describes the deviation of the dam, is constructed based on three important factors: time-evolution of the phenomenon (consolidation or degradation trends), hydrostatic and thermal effects, respectively (Gentil S. and Popescu D. 1998).

2) A partial evaluation of the dynamical models on five observation intervals. The input data measurement (*u (k)* - the hydrostatic pressure) and the output of the system (*y (k)* - the deviation of the dam) is divided in five partitions in order to apply a usual identification method, Recursive Least-Squares (RLS). The parametric estimation for a partition is used for the initialization of the next one. According to this method, the final estimation gives out the dynamics of the system for the whole period of time (Isermann, 1986; Bittanti and Lovera, 1997, Soderstrom and Stoica, 1989; Astrom and Nilsson, 1994).

2. ANALYSIS OF THE MULTIVARIABLE MODEL

We consider the superposition of the main three states:

- An irreversible state for the time-evolution of the phenomenon; this evolution can be redeemable (a consolidation trend) or become accelerated (degradation);
- A reversible state according to the hydro-static pressure at the level *h* of the water in the dam;
- A reversible state in order to consider the effect of the temperature repartition θ in the dam.

The definition of the model is based on the sum of these three independent effects. We define 3 functions: $f_1\ (t), f_2\ (h), f_3\ (\theta)$, so that the value of the deviation *Y* is:

$$Y = f_1\ (t) + f_2\ (h) + f_3\ (\theta) + \varepsilon \qquad (1)$$

With t, h, θ the values in the corresponding measurement day and ε includes the experimental errors and all the other side effects.

2.1 Mathematical structure of the model

The experience on the dam deviation phenomenon leads to the following structures of the functions:

1) $f_1(t)$ function
The formula includes a negative exponential term for modeling of the redeemable evolution and a positive exponential term representing the accelerated evolution:

$$f_1(t) = b_1 \exp\ (-t) + b_2 \exp(t) \qquad (2)$$

2) f_2 (h) function
The modeling of the hydro-static pressure in the dam is obtained by using a 4-degree polynomial function with the flood-level variable *Z* defined by $Z = (RN-h)/H$, where *h* is the level of the water in the dam, *RN* is the normal level and *H* is the altitude of the dam.

$$F_2(Z) = b_3 Z + b_4 Z^2 + b_5 Z^3 + b_6 Z^4 \qquad (3)$$

This flood-level variable counts values between 0 and 1 and sets the full-state of the dam as the reference hydrostatic state ($f_2\ (Z) = 0$ for $Z=0$ it means $h=RN$).

3) f_3 (θ) function
The thermal state of the dam is practically the same, each year, at the same date and depends only on the season variable *S*. The seasoning function used instead of the thermal function $f_3(S)$ is a periodic function of time. The variable

S is an angle starting at 0 degrees for the 1st of January and ending at 360 degrees for the 31st of December. A cosine function in S with an unknown phase ϕ is used in addition with a cosine function in $2S$ with an unknown phase φ for modeling the possible dissymmetry.

$$f_3(S) = \alpha \cos(S+\phi) + \beta \cos(2S+\varphi) \quad (4)$$

2.2 Global model representation

For obtaining a stochastic consistent set of data we used:
- Exponential filtering for excluding measurement errors;
- Filtering noise measurement;
- A reduction for the time variable in the function $f_1(t)$ based on the arbitrariness of the time-origin for the accelerated and redeemable evolutions in this function. The reduced function has the form:

$$f_1(t) = b_1 \exp(-t)/\exp(-t_1) + b_2 \exp(t)/\exp(t_2), \quad (5)$$

With t_1 - a data in the proximity of the first measurement and t_2 - a data at the end of the year corresponding to the last measurement;
- The developing of the function $f_3(S)$ in terms of the seasoning variable S:

$$f_3(S) = b_7 \cos(S) + b_8 \sin(S) + b_9 \sin^2(S) + b_{10} \sin(S)\cos(S) \quad (6)$$

We consider the hydro-energetic system as an input-output system with the inputs z (z_1, z_2, z_3), where z_1 is the time, z_2 is the hydrostatic pressure at the level h and z_3 is the temperature. The output y is the deviation of the dam. With these considerations the non-linear structure of the multivariable model of the dam deviation is:

$$\hat{y}(z) = f_{1n}(z_1) + f_{2n}(z_2) + f_{3n}(z_3) \quad (7)$$

or, using the following substitutions:

$$\begin{aligned} x_1 &= e^{-z_1} & x_6 &= z_1^{\ 4} \\ x_2 &= e^{z_1} & x_7 &= \cos z_3 \\ x_3 &= z_1 & x_8 &= \sin z_3 \\ x_4 &= z_1^{\ 2} & x_9 &= \sin^2 z_3 \\ x_5 &= z_1^{\ 3} & x_{10} &= \sin z_3 \cos z_3, \end{aligned} \quad (8)$$

We obtain a linear model $\hat{y}(x)$.

2.3 Identification of the model parameters

The method used here is the Least-Squares method. We show the linear case by using the inputs of the model.

Let us consider a process with n inputs, $x=(x_1, x_2 \dots x_n)$ and the output y. After the synchronous acquisition of measurements we have the data in a matrix form:

$$X_m = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & & \vdots \\ x_{N1} & x_{N2} & \cdots & x_{Nn} \end{pmatrix}, \mathbf{Y} = \begin{pmatrix} \mathbf{y}_1 \\ \mathbf{y}_2 \\ \vdots \\ \mathbf{y}_N \end{pmatrix} \quad (9)$$

Where:

X_m is the matrix of the inputs

Y is the output vector.

x_{ij} is the value of the component j (j=1, n) for the measurement i (i=1,N),

y_i is the value of the output for the measurement i (i=1,N).

We associate to this process the linear model of parameters $\hat{b}$:

$$\hat{y}(x) = \sum_{i=1}^{n} \hat{b}_i x_i = \hat{b}^T x . \quad (10)$$

After computing the estimation $\hat{b}$ it is necessary to validate the model. In the case when the model cannot be validated we have to use an adaptive procedure in order to re-estimate the parameters. We introduce the significant index R^2 in order to measure the precision degree of modeling:

$$R^2 = \frac{\sum_{i=1}^{N}\left[\hat{y}_i - \bar{y}\right]^2}{\sum_{i=1}^{N}\left[y_i - \bar{y}\right]^2}.$$

(11)

In this relation we have:

$\hat{y}_i$ - The output value computed for the model (10) with y_i the value of the process output for the measurement *i*,

$\bar{y}$ - The mean value of the outputs of the process:

$$\bar{y} = \frac{1}{N}\sum_{i=1}^{N} y_i .$$

(12)

If the value of R^2 is in the interval (0.7, 1) then the model can be validated. The validation of the results given by the parameters estimation $\hat{b}$ is made using the index R^2.

The results shown in the Appendix 1 (for n=10 inputs and M=1200 measures) were obtained in simulation with our software package (SISCON) using the LS method for the multivariable non-linear case.

3. DISCRETE TIME MODELS EVALUATION

In this section first we will consider the hydro-energetic system in a continuous input-output form given by: the input *u(t)* (the level of the water in the dam), the output *y(t)* (the deviation of the dam) and *p(t)* the disturbance (a random process for modeling the effect of the exterior temperature and the other seasoning phenomena with thermal and hydro-dynamic effects).

3.1 The structure of the discrete time models

We associate with the above mentioned process a dynamical discrete-time model:

$$B\left(q^{-1}\right)y(k) = A\left(q^{-1}\right)u(k) + C\left(q^{-1}\right)e(k), \quad (13)$$

Where:

u(k) - the set of the discrete values of the input *u(t)*,

y(k) - the set of the discrete values of the output *y(t)*,

e(k) - a white-noise signal generating the discrete values for the disturbance *p(t)*.

The input *u (k)* is a measurable perturbation for the open-loop system. For this structure we propose an efficient procedure for estimating the parameters of the discrete-time model (the evaluation of the polynomial coefficients of *A* (q^{-1}), *B* (q^{-1}), *C* (q^{-1})), using the RLS method.

3.2 RLS parameter estimation

The strategy of parametric evaluation uses recursive adaptive estimation techniques. If we denote by $\hat{\theta}(k+1)$ the vector of the estimation, by $\phi(k)$ the vector of data and by $\varepsilon(k+1)$ the prediction error, the recurrent relation is:

$$\hat{\theta}(k+1) = \hat{\theta}(k) + F(k+1)\phi(k)\varepsilon(k+1) .(14)$$

$F(k+1)$ is the matrix of the adaptive gains at each step of modifying the parameters $\hat{\theta}(k)$. The recurrent relation for $F(k)$ is:

$$F(k+1) = F(k) - \frac{F(k)\phi(k)\phi^T(k)F(k)}{1+\phi^T(k)F(k)\phi(k)} ,(15)$$

with the initialization $F(0) = \alpha I$, $\alpha > 0$ and *I* the unit matrix. The algorithm of adaptive parameterization may be initialized by $\hat{\theta}(0) = 0$, when we don't have any information about $\hat{\theta}$ (Dauphin-Tanguy, *et al.*, 2004).

Concluding, the identification of the dynamical model's parameters by the RLS method uses the following equations:

$$\begin{aligned} &\hat{\theta}(k+1) = \hat{\theta}(k) + F(k+1)\phi(k)\varepsilon(k+1) \\ &F(k+1) = F(k) - \frac{F(k)\phi(k)\phi^T(k)F(k)}{1+\phi^T(k)F(k)\phi(k)} \\ &F(0) = \alpha I , \ \alpha > 0 \end{aligned} \quad (16)$$

3.3 Validation of the discrete time models

Considering the random disturbance as a white noise, we can perform the validation test, based on the whiteness of the prediction error, by controlling the values of the auto-correlation function given by:

$$R(i) = M[e(k)e(k-i)] = \lim_{N\to\infty}\frac{1}{N}\sum_{i=1}^{N}[e(k)e(k-i)]$$

(17)

Where R (i) is the covariance function (auto-correlation) for a deviation of sequence e (k) with i steps. The covariance is:

$$RN(i) = \frac{R(i)}{R(0)} \quad (18)$$

For a Gaussian white-noise the sequence of these variables is independent, and due to the ergodic character of the random process, the validation test is:

RN (0) =1 and RN (i) =0, $i = \overline{1,k}$.

In practice, the test conditions are:

RN (0) =1 and $RN(i) \le \gamma_i$ with $\gamma_i \le 0.1$.

In the study case of Tarnita dam we proposed a 2nd order discrete-time model with:

$$A(q^{-1}) = 1 + a_1 q^{-1} + a_2 q^{-2};$$
$$B(q^{-1}) = b_1 q^{-1} + b_2 q^{-2};$$

(19)

$$C(q^{-1}) = c_1 q^{-1} + c_2 q^{-2}$$

The initialization for $\hat{\theta}(0)$ was chosen in the origin of the parameter space, with $F(0) = \alpha I$ ($\alpha = 1000$). The simulated results were obtained by PIM software for experimental recursive identification and they are presented in Appendix 2 (Landau, 1995).

4. CONCLUSIONS

A global model describing the evolution of the deviation of the hydro-energetic dam has been evaluated from data measured between 1989 and 2009. The evolution has a stabilization tendency.

The analysis of the results obtained from the global model proves that the studied hydro-energetic system has a slow evolution with the trend to a stationary position. A dynamic model for each of the five intervals of interest has been obtained by using experimental recursive techniques (RLS).

The evaluation of the behavior of the dam using dynamical models for these intervals shows some non-periodical evolutions characterized by inertia in addition to an effect of inverse response model. The effect of inverse response model denotes that a good consolidation system can be realized not on the back, bat on lateral sides of the dam.

All this information has been used for the evaluation of the dam dynamic phenomena and for the present design and exploitation of the hydro-energetic systems in Romania.

Appendix 1. The results of the evaluation of the global model using the LS off-line method

The evolution interval for the data measurement is 11/11/1989-12/29/2009. For modeling the irreversible evolution of the dam in the reduced form (the function f_1 (t)) we use:

- t_1 - the data of the first measurement (11/12/1985);
- t_2 - the data of the last measurement (12/29/2005).

The polynomial function f_2 (Z) was computed using the formula:

Z= $(RN$-$h)/H$, with RN=521.5, H=97.

The results of the global model parameters are illustrated in Table 1.

Table 1 Parameters ‘values

Estimated parameter	Value
b_0	-41.445
b_1	12.818
b_2	-5.142
b_3	-37.740

b_4	414.231
b_5	-1279.173
b_6	994.583
b_7	-1.395
b_8	-7.060
b_9	-1.245
b_{10}	-0.206
Index R^2	0.916

The output evolutions of the dam deviation y and its identified model are presented in Fig. 1.

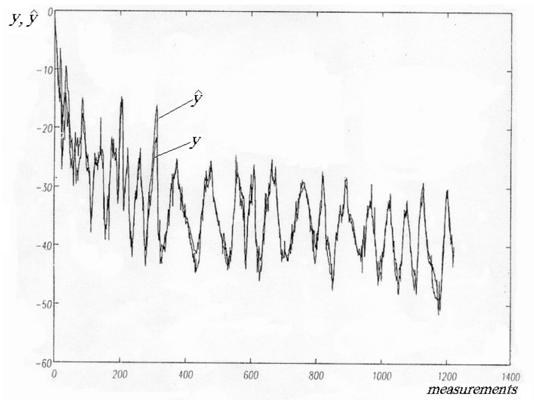

Fig. 1. Output for the dam (y) and its model ($\hat{y}$).

Appendix 2. The results of the evaluation of the discrete time models using the RLS method

For five intervals of time, we have computed the coefficients of the polynomials A (q^{-1}), B (q^{-1}), C (q^{-1}), it means the discrete-time model on each interval and the values for the normalized auto-correlation functions associated with these models.

- Interval 1: 11/12/1989 - 07/04/1993

$A(q^{-1})$	$B(q^{-1})$	$C(q^{-1})$
a_1=-3.68	b_1=-106.74	c_1=-0.324
a_2=2.688	b_2=107.81	c_2=0.088

$RN(0)$	$RN(1)$	$RN(2)$	$RN(3)$	$RN(4)$
1.000	0.033	-0.026	0.068	-0.002

- Interval 2: 07/13/1993 - 12/24/1996

$A(q^{-1})$	$B(q^{-1})$	$C(q^{-1})$
a_1=-1.39	b_1=-0.128	c_1=-0.47
a_2=0.40	b_2=-7.588	c_2=0.05

$RN(0)$	$RN(1)$	$RN(2)$	$RN(3)$	$RN(4)$
1.000	0.0155	-0.007	0.02	-0.07

- Interval 3: 12/27/1996 - 08/31/2000

$A(q^{-1})$	$B(q^{-1})$	$C(q^{-1})$
a_1=-0.98	b_1=1.31	c_1=-0.03
a_2=-0.006	b_2=-11.44	c_2=0.02

$RN(0)$	$RN(1)$	$RN(2)$	$RN(3)$	$RN(4)$
1.000	-0.004	0.0002	0.06	0.027

- Interval 4: 09/01/2001 - 05/02/2004

$A(q^{-1})$	$B(q^{-1})$	$C(q^{-1})$
a_1=-0.819	b_1=3.593	c_1=0.172
a_2=-0.169	b_2=-12.659	c_2=-0.002

$RN(0)$	$RN(1)$	$RN(2)$	$RN(3)$	$RN(4)$
1.000	-0.001	-0.007	0.02	0.045

- Interval 5: 05/16/2005 - 12/29/2009

$A(q^{-1})$	$B(q^{-1})$	$C(q^{-1})$
a_1=-1.124	b_1=3.342	c_1=-0.108
a_2=0.126	b_2=-4.203	c_2=0.021

$RN(0)$	$RN(1)$	$RN(2)$	$RN(3)$	$RN(4)$
1.000	0.0005	-0.0009	-0.0052	0.0062

REFERENCES

Astrom K. and J. Nilsson (1994), Scheme of Iterated Identification and Control, *Proc.*

SYSID'94, 10-th IFAC Symposium on System Identification, Vol. 2, pp. 171-176.

Bittanti S. and M. Lovera (1997), Identification of Linear Models for a Flexible Structure, *Preprints of IFAC SSC'97 Conference*, pp. 138-142.

Dauphin-Tanguy G., L. Foulloy and D. Popescu (2004), *Modelisation, Identification et Commande des Systems*, Ed. Academiei Romane, Bucharest.

Isermann R. (1986), Practical Aspects of Process Identification, *Automatica*, no. 16, pp. 575-587.

Landau I. D. (1995), *Identification et Commande des Systèmes*, Hermès, Paris.

Soderstrom T. and P. Stoica (1989), *System Identification*, Prentice Hall, London.

Dion J.M., Popescu D. – *Optimization des Systems - Commande Optimale*, Diderot, Paris, France, 1997.

Gentil S., Popescu D., - *Commande Numerique et Intelligence Artificielle en Automatique*, Ed. Tehnica, Bucharest, Romania, 1998

Goodwin G.C., Payene R.L. – *Dynamic System Identification: Experiment Design and Data Analysis*, Academic Press, New York, 1977.

Popescu D., Stefanoiu D. and all – *Industrial Control* - , Ed. Agir, Bucharest, Romania, 2007