Nonlinear identification of electrohydraulic servovalve using genetic algorithm

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Abstract

This work presents a nonlinear identification approach for electrohydraulic servovalves, common in aerospace actuation systems. The methodology is based on a *Genetic Algorithm* which the cost-function is related to the error between the identified model and the real system. The method searches the linear and nonlinear parameters such that the cost-function above reach a minimum value, what implies that the model is close to the real system. The approach is validated through simulation results of a known servovalve model.

1. Introduction

Electrohydraulic servovalves (EHSV) are widely applied on linear and angular servomechanisms, and the knowledge of its dynamics is essential to control system design. Several works cover the aspects about EHSV's, showing internal moving parts, its motion equations and the most important nonlinearities.[4,6] Servovalves are specially useful as the main actuator element of aerospace systems; particularly in launchers it operates like in the thrust vector control actuation for solid propelled vehicle or in gimballed chamber for liquid propelled rockets. Since their influence over the aerospace vehicle control loops, a precise modelling of EHSV linear and nonlinear behaviours is primary to a proper launcher performance.

The genetic algorithm (GA) use evolution ideas taken of the nature in optimisation processes. There are excellent references about this approach[7,8] that present the computational details and applications. Although the genetic algorithm is extensively used in optimisation, some works have discussed it for identification purpose. The most used idea is comparing the real input-output signal with those obtained by the estimated model, where the GA is used to tune the model parameters until that an behaviour similar to the real system is reached.[2] This approach does not need linearity over the parameters and differentiability of the functional to be optimised – both are important issues in a *lest-squares* methodology. In an identification procedure, the GA has the advantage of direct model simulation, since the present simulation model facilities provided by tools like Mathworks' Simulink©.

For the identification of nonlinear systems, the use of genetic algorithm is particularly attractive because a formal formulation that relates the model parameters with a output functional is very hard to find. There are some interesting applications in the literature like a 2-mass resonant vibration system, a parameter identification of a exciting power system and nonlinear identification by Volterra filtering.[1,3,9] Some hybrid evolutionary / recursive methods are also proposed.[5]

In this paper, an approach for identification of nonlinear aerospace servovalves based on genetic computation is presented. The theory involved with hydraulic servovalves is discussed as well the necessary assumptions to the system identification. Finally the methodology is applied to the nonlinear identification of a hydraulic servovalve model with known parameters.

2. Electrohydraulic servovalves modelling

The EHSV consists of a powerful component in control systems that joints the versatility of electrical components with hydraulic actuators performance at high power levels. In this way, several dynamic effects are present and one should pay attention to some details in the modelling procedure.

2.1 Turbulent orifice flow and linearised analysis of valves

The turbulent flow through an orifice occurs at high Reynolds number and is modelled applying the Bernoulli's equation. This analysis yields the following well-known volumetric flow rate:

$$Q = C_d A_0 \sqrt{\frac{2}{\rho}(P_1 - P_2)} \tag{1}$$

where C_d is the discharge coefficient, A_0 the orifice area, ρ the mass density of fluid and $(P_1 - P_2)$ the pressure drop. Considering a typical four-way spool valve where the orifice areas depend on valve geometry, their four areas are functions of valve displacement x_v. The load flow as a function of valve position and load pressure is given by the nonlinear relation

$$Q_L = Q_L(x_v, P_L) \tag{2}$$

known as the *pressure-flow curves* and is a complete description of steady-state valve performance. This nonlinear algebraic equation is linearised to dynamics analysis, using a concatenated Taylor's series about a particular operating condition. Thus the linearised equation on Laplace's notation becomes

$$Q_L(s) = K_Q x_v + K_C P_L \tag{3}$$

where K_Q and K_C are the most important parameters and are obtained by differentiation of the equation for the pressure-flow curves or graphically from a plot of the curves, as presented in figure 1, that shows them in a normalised manner.[6] The flow gain is defined by $K_Q \equiv \partial Q_L/\partial x_v$ and the flow-pressure coefficient $K_C \equiv -\partial Q_L/\partial P_L$. The load flow equation is given as follows, considering an ideal critical centre valve:

$$Q = C_d w x_v \sqrt{\frac{1}{\rho}(P_S - \frac{x_v}{|x_v|} P_L)} \tag{4}$$

where P_S is the supply pressure to valve.

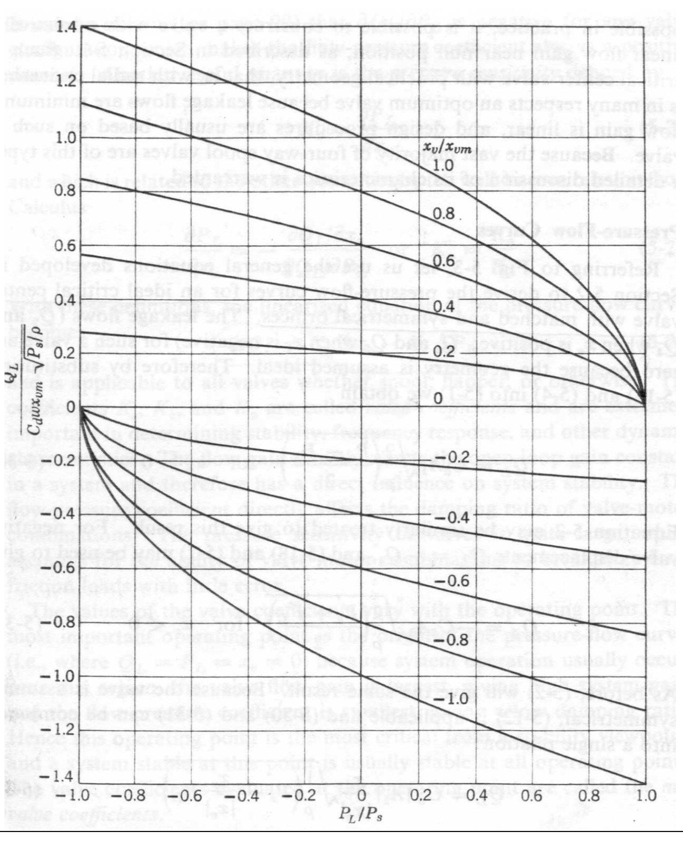

Figure 1: Normalised pressure-flow curves.

2.2 Flow forces on spool valves

The fluid flowing through uncompensated valve orifices causes forces with a direction such that it tends to close the valve port. The magnitude of this force is given by:

$$F_1 = 2C_d C_v A_0 (P_1 - P_2) cos(\theta) \tag{5}$$

where, typically $\theta \approx 69°$ is the jet angle of vena contracta, $C_d = 0.61$ the discharge coefficient, $C_v = 0.98$ the empirical factor called *velocity coefficient* and $\Delta P = P_1 - P_2$ the pressure drop. Considering the area gradient of the valve, $w \equiv \partial A / \partial x_v$, $[w] = m^2/m$, and the numerical values above yields the usual form of the steady-state flow force equation:

$$F_1 = 0.43 w \Delta P x_v = K_f x_v. \tag{6}$$

Merritt[6] comments that on larger single stage EHSV (four-way, $1in.$ diameter spool, $0.020in.$ stroke, and $P_S = 1000psi$ this force can exceed $20lb$ ($9kgf$). The reduction of this steady-force flow force can be obtained using two-stage configuration or using geometric compensating techniques. These compensations can lead to nonlinear flow force versus stroke characteristic.

2.3 Continuity equation

The fundamental laws and the complete fluids flow equations are the basis to the complete knowledge for the hydraulic modelling and identification process. Mathematical models to the three directions of motion are obtained from Navier-Stokes equations and law of conservation of energy. The continuity equation combined with the equation of state ($\rho = \rho(P, T)$) leads to the following expression, in Laplace's notation

$$\sum Q(s) = s\left(V_c + \frac{V_C P}{\beta}\right) \tag{7}$$

where β is the Bulk modulus (for mineral oils and for common values for pressure and temperature, β is typically 1400 to 1600 MPa). The equation above is the general form with variable chamber volume. In the case of constant V_c leads to

$$\sum Q(s) = s\frac{V_C P}{\beta} \tag{8}$$

where V_C/β is equivalent to a linear hydraulic capacitance, known as C_H. In case the EHSV is mounted directly on the actuator and the high pressure lines are sufficiently short, then the hydraulic capacitance can be considered negligible.

Using all equations above, one can express the EHSV model as shown in block diagram in figure 2. In this model, the linear transfer function expresses the feedback controller that, in a electrohydraulic servovalve, is implemented by electronic circuitry. The load is composed by a mass-spring system.

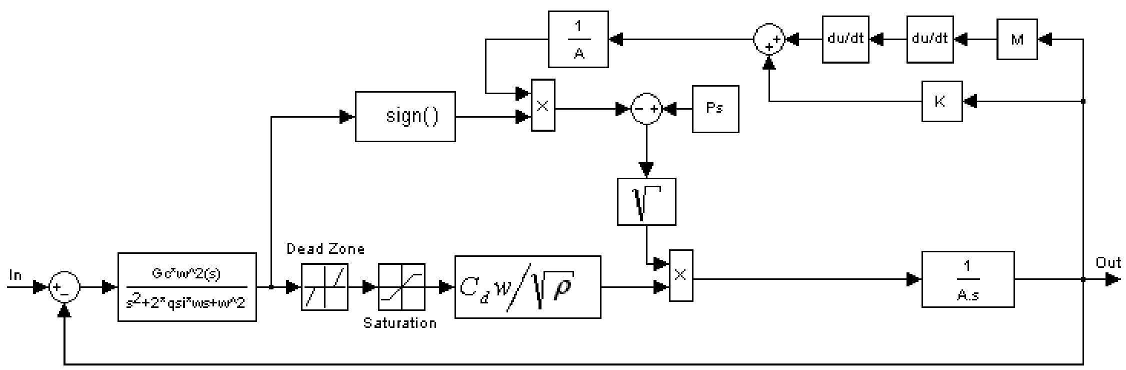

Figure 2: EHSV block diagram

3. Genetic Algorithm and Nonlinear Identification

In this section, a brief discussion about the genetic algorithms as well its application for optimisation are discussed. After, it will be presented a methodology to use the genetic optimisation for the identification of nonlinear systems. The method will be validated by applying it for the Van der Pol system identification.

3.1 The Genetic Algorithm

The **Genetic Algorithms** are optimisation processes based on evolution ideas taken of the nature. Then, the GA's are characterised by the evolution of an initial set of solutions, named *population,* according to stochastic rules that lead the actual population to the next, in a *generation* sequence. Different of other optimisation processes, the genetic algorithm works with many candidate solutions chosen randomly in a search space defined by the user. The user can select the number of solutions used on the optimisation (called *population length*) or N_{pop} and the maximum number of generations N_{gen} before the process.

This population is coded such that the *genetic operations* below can be applied. Basically, there are two ways of codification: the binary codification where each solution is coded by a binary code with a previous-defined number of bits, and the real-polarised code where each solution is coded according to a proper real equation relationship.[7] In this paper, the last codification is adopted.

A set of operations over the coded elements were developed such that the population evolution is similar to the evolution of a colony in the nature. The basic GA operations are:

i crossover: it combines the informations contained in two or more elements, such that new solutions are created. This operator is useful to guide the population for a possible global minimum after some generations;

ii mutation: a new solution is created by using a stochastic rule to modify an element. The mutation operator guarantees the diversity of solution set. Then, new regions in the search region can be explored;

iii selection: some elements are replicated and continue to the next generation according to a fitness function. The others are discarded;

iv elitism: if the best solution is not selected to the next generation, it can be inserted by replacing another element that is chosen randomly.

The genetic optimisation applies the operations *i*, *ii* over the initial population. Then a cost-function associated to the functional minimum proximity is evaluated and each element is marked. According to their marks, the operations *iii* and *iv* select the elements to the next generation and new elements are randomly added if is necessary. After each generation a stop test is performed. The algorithm is finished case the solutions are sufficiently close of the minimum or the maximum generation number is reached, otherwise the same genetic operations are applied over the new population and so on. This method results in the convergence of the population to the functional minimum after some generations. The pseudo-code below summarises the optimisation procedure.

```
Choose an initial parameter set S(x) with length Npop

for i = 1 to Ngen {
Apply a codification over S(x);
Execute the crossover and mutation operations;
Evaluate a cost-function related to the functional to be minimised;
Execute the selection and elitism operations to produce the new S(x);
If it is necessary, add new random elements to S(x);
Execute the stop test;
}
The best element of S(x) is the solution of the optimisation procedure.
```

3.2 Identification of Nonlinear Systems

In this section, it will be presented the use of genetic algorithms for identification purpose. The idea is similar to an optimisation process and can be seen better in the Figure 3. The algorithm produces an initial model set by choosing a population of parameters, and then each model is simulated with the same input signal applied over the real system. After, a cost function related to the error signal (e) between the model output and the real system is computed. The cost function used on this paper is the error signal norm, expressed by

$$J = \int_0^{T_{final}} e^2(t)dt, \tag{9}$$

where T_{final} is the simulation final time (same of the experimental data). The cost function values are used by the genetic algorithm to produce a new parameter set, based on the genetic operations yet discussed. After some generations

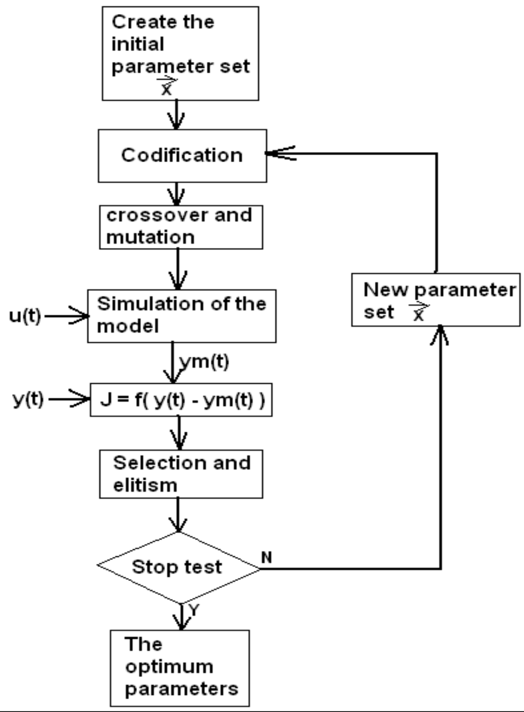

Figure 3: Flowchart of genetic algorithm used to the nonlinear identification

the optimisation converges to the best set of parameters such that the error between the model and the system have the slower norm; this produces the best model, obviously limited to the chosen model structure.

A known model should be used to validate the identification procedure. For this purpose, it was chosen the following Van der Pol oscillator.

$$\begin{cases} \dot{x}_1 = \alpha x_2 \\ \dot{x}_2 = -x_1 + \gamma(1 - x_1^2)x_2 + u \\ y = x_1 + \xi \end{cases} \tag{10}$$

where $\alpha = 0.96$, $\gamma = 1.23$ and u is a *pseudo random signal*, PRS. This signal is closely related to the traditional *pseudo random binary signals*, but with a random amplitude too; the amplitude variation is important to detect system nonlinear effects that can be hidden if only a fixed amplitude was used. The system with these conditions was simulated and the output y was corrupted by a mean zero gaussian measurement noise ξ. The obtained signals are used to emulate an experimental data and are applied to the α and γ genetic identification with $N_{gen} = 50$ and $N_{pop} = 100$. Two measurement gaussian noises with variance 0.05 and 0.1 respectively are used and the results are presented in the table 1.

Table 1: Genetic identification of the Van der Pol oscillator.

Noise Variance	$\hat{\alpha}$	$\hat{\gamma}$
0.05	0.9606	1.2345
0.1	0.9307	1.1337

Note that the α and γ estimated values were very similar to the real ones when the measurement noise has variance 0.05. More significant differences occur when a harder measurement noise is used, but the model response is yet close to the expected model, as shown in the figure 4.

The results above confirm the genetic algorithm efficiency for nonlinear identification even in a noisy scenario. Despite of this, one should pay attention to some details for the identification success.

i) <u>The Model Structure</u> is the most important factor for a good identification. In the example, it was used the exact equations that represent a Van der Pol oscillator. Obviously, same results are not reached if other mathematical

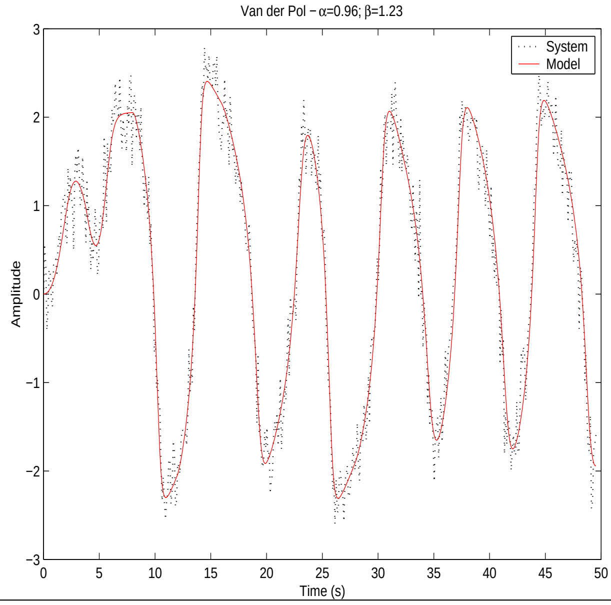

Figure 4: Identification of the Van der Pol oscillator. The experimental signal is corrupted by a gaussian noise with variance 0.1 Note that the model has a proper behaviour.

formulation was used, what suggest a previous study of the system before the identification. If this is not possible, it can be necessary some effort to obtain an equation set that represent the system approximately.

ii) The parameters search space is another source of problems. The question is 'in which region one should search the parameters?' or better 'which the interval should be selected for each parameter during the search?' The immediate answer would be 'bigger as possible' but this can result in slow parameter convergence and model stability problems. The best approach is selecting the intervals based on previous system knowledge or through a trial-and-error procedure for a completely unknown system. Careful should be also taken with the number of parameters to be identified, since that the search space dimension affects the parameter convergence.

4. Simulation Results

This section presents the simulation results of the nonlinear identification applied to the servovalve case. The AG algorithm runs in the Matlab© and the model simulation is constructed based on Simulink© block diagram. The "real" signals are obtained by previous simulation of the known model with output corrupted by a gaussian measurement noise with proper variance. These informations are used in the identification process as follows.

In a real situation when the user has a mounted servovalve with a known load, the identification procedure begins with tests to collect the output signals, that represent the system behaviour. After, a reasonable nonlinear representation that includes the most important linear and nonlinear effects should be assumed, resulting in a model structure for the optimisation process. Finally, a computational procedure is implemented to apply a genetic optimisation to identify the unknown parameters. Particularly for this paper, a known model is assumed and then the approach validity is tested.

The model used in the genetic identification was presented in figure 2, and the hypothetical parameter set is presented on the table 2. A *Pseudo Random Signal* was used to excite the system and then one can collect the output signal to be used in the identification process.

At this stage, one has already the complete structure of the identification problem including the chosen nonlinear block diagram, the parameters to identify, etc. At the specific servovalve case, a proper block diagram to be used in the identification process is presented in figure 2. It contains *constant parameters* that are assumed known. This parameters are the cross section of valve piston $A = 25\times10^{-4}m^2$, the supply pressure $P_s = 140bar$, and the load system described by its mass $M = 20kg$ and the spring constant $K = 1 \times 10^4 N/m$. The coefficients to be identified are the feedback parameters (Gc, ξ and ω), the hydraulic constant $H = C_d w/\sqrt{\rho}$ and the nonlinearities expressed by the spool dead zone and saturation.

A gaussian measurement noise with three different variances was added to the signal to become the simulation example more realistic. The genetic optimisation parameters were selected as $Npop = 50$ and $NGen = 20$ and the interval search for each coefficient was chosen around 50% of its known value. These intervals take important influence in the algorithm convergence in a real identification, such that repeated optimisations can be necessary to their selection. The results of the genetic identification in these conditions are presented on the table 2.

Table 2: Genetic identification of the servovalve system.

	dead zone (m)	saturation (m)	H $((m^3/kg)^{1/2})$	G_c (m/m)	ξ	ω (rad/s)
Real	1×10^{-4}	3×10^{-3}	1×10^{-5}	0.09	0.72	300
Variance 1×10^{-8}	9.92×10^{-5}	3.0×10^{-3}	1.41×10^{-4}	0.0919	0.6647	296.35
Variance 1×10^{-7}	9.21×10^{-5}	2.0×10^{-3}	1.4×10^{-4}	0.0872	0.7418	327.6
Variance 1×10^{-5}	1.2×10^{-4}	3.8×10^{-3}	1.58×10^{-4}	0.0909	0.7145	265.93

This table shows a good convergence, but some parameters show itself more sensitive to the measurement noise. Despite of this, the modelled and “real” systems have a very similar behaviour, as can be seen in the figure 5 even in a so noisy environment like in the right figure.

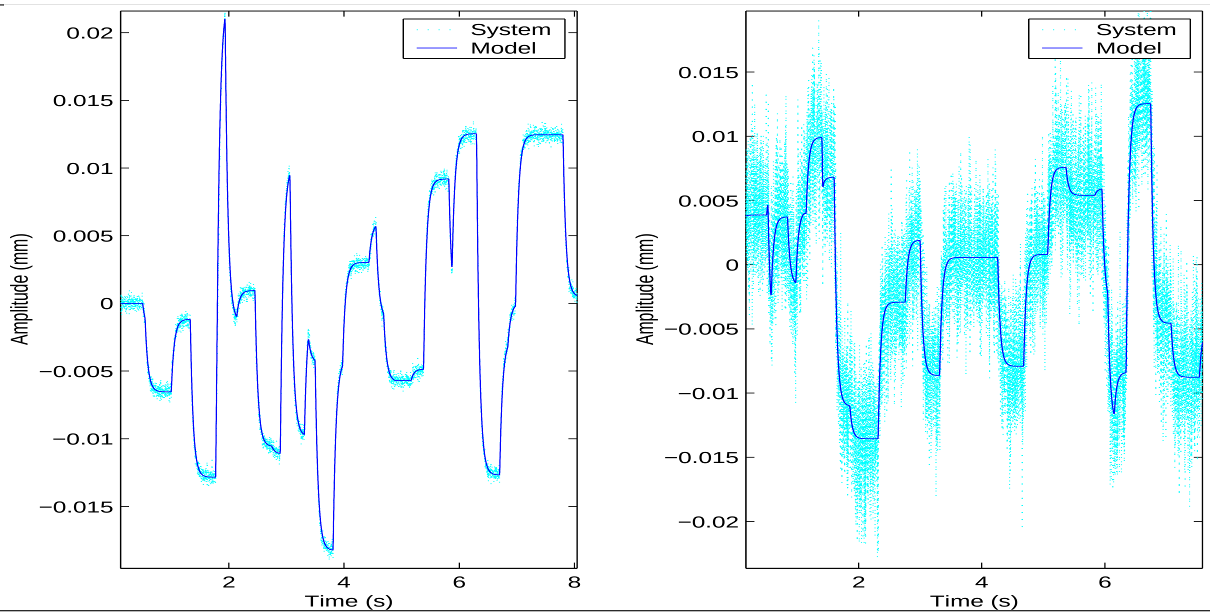

Figure 5: Genetic Identification of the known servovalve model. The left figure presents the results for a measurement noise with variance 1×10^{-7}. In the right, the noise variance is 1×10^{-5}.

5. Conclusions

This paper presented a methodology for nonlinear identification based on genetic optimisation. The objective is obtaining a nonlinear model for electrohydraulic servovalves, very common in control loops of aerospace vehicle like aircrafts and launch vehicles. The EHSV has important nonlinearities that can become its behaviour quite different of a traditional linear models. So, a proper nonlinear identification procedure is primary to control purpose.

The nonlinear identification with genetic algorithms was applied in a hypothetical servovalve with known parameters. It was supposed that the system can be affected by three different levels of measurement noise, used to validate the approach in a real modelling situation. In all cases, the identified parameters presented good accordance to the known values, even in the worst noise environment as can be seen in the figure 5.

Obviously, the procedure needs improvements. Some pitfalls were found in algorithm convergence due to the EHSV structure adopted, were the load is written as a derivative feedback. This brings a lot of problems with the differential equation solver such that the integration method and the simulation step must be selected carefully. Overall, variable-step integration should be avoided. Other practical question is related to the solution space search that can not be much wide to avoid slow convergence to the correct values. If the user doesn’t have previous knowledge of the size of the space search, a cut-and-try procedure can be used until a proper space is found.

The next step will be studying the method use for the model identification of a real servovalve benchmark, similar to common aerospace actuation systems. We believe that the approach will present good performance, overall after the improvements discussed above.

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