

# Study of Parameter Identification Using Hybrid Neural-Genetic Algorithm in Electro-Hydraulic Servo System

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This paper demonstrates that hybrid neural-genetic multi-model parameter estimation algorithm. This method can be applied to structured system identification of electro-hydraulic servo system. This algorithms consist of a recurrent incremental credit assignment(ICRA) neural network and a genetic algorithm. The ICRA neural network evaluates each member of a generation of model and genetic algorithm produces new generation of model. To evaluate the proposed method, electro-hydraulic servo system is designed and manufactured. The experiment is carried out to figure out the hybrid neural-genetic multi-model parameter estimation algorithm. As a result, the dynamic characteristics are obtained such as the parameters (mass, damping coefficient, bulk modulus, spring coefficient), which minimize total square error. The result of this study can be applied to hydraulic systems in industrial fields.

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## NOMENCLATURE

$K_a$  : Servo Amp. gain [mA/V]  
 $M$  : Mass [kg]  
 $B$  : Viscosity coefficient of cylinder [Nm/sec]  
 $K_s$  : Spring coefficient [N/m]  
 $C_d$  : Discharge coefficient  
 $F_L$  : Disturbance  
 $w$  : Area Gradient [m]  
 $x_v$  : Spool displacement [m]  
 $V$  : Total Volume in cylinder [m<sup>3</sup>]

## 1. Introduction

Enhanced functionality of measurement instrument using modern digital technologies has led to highly precise and reliable controllers for hydraulic systems. Electro-hydraulic servo systems, taking the advantages of the hydraulic and electro signal processing, are

attracted significant attention in the industrial field. However, the electro-hydraulic servo systems suffer two major difficulties: (a) nonlinearities caused by input saturation, directional change of valve opening, oil leak, or friction; and (b) fluctuation in the system parameters due to the time-varying environment such as changes of load condition and the bulk modulus, or variable temperature. Many researchers have addressed various empirical methods for identifying the parameters of electro-hydro servo systems [1], [2] and [3]. For example, Navid[1] proposed a robust force controller based on a linearized model of which parameters are estimated using a set of input-output data. For hydraulic suspension systems, Tan[2] has obtained the model equation by applying an input-output data based parameter identification technique to each sub-component, while Majjad[3] attempted to estimate the damping

characteristics. Unfortunately, most of the previously addressed work has focused on identification of the models for control requiring a relatively simple model. They used a least squares algorithm where it is difficult to find global solutions. Therefore, this paper presents a parameter identification method based on a hybrid neural-genetic algorithm that can provide a global solution. Using a set of input-output data obtained through experiments, the proposed method estimates the system parameters of a nonlinear electro-hydraulic servo system, such as mass, damping coefficient, spring constant and bulk modulus. The effectiveness of the proposed algorithm is demonstrated on an example electro-hydraulic system.

## 2. SYSTEM MODELING

### 2.1 Electro-hydraulic servo-system

Figure 1 shows the example electro-hydraulic servo system designed in this work. The system is designed to operate under various inertia load conditions. The spring-damper system and the hydraulic cylinders are installed in a parallel structure with a clevis bearing which distributes the load vertically.



Fig. 1: Schematic of electro-hydraulic servo-system

The spring and damping system, which are used, are taken from a suspension system of vehicles. The hydraulic cylinder is a single-rod cylinder with 140 mm stroke. The displacement is measured with a potentiometer with a 12-bit A/D and D/A board. The entire system is controlled by a personal computer with 66 MHz clock speed. The position controller of the system is described in Fig.2.

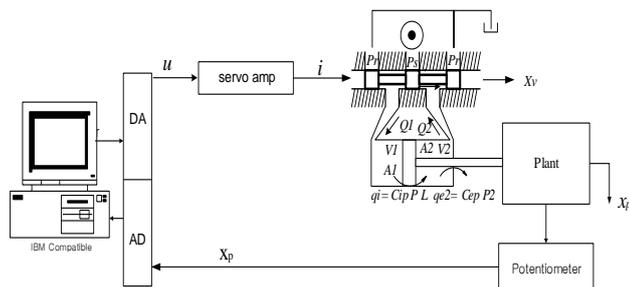


Fig. 2 Schematic diagram of electro-hydraulic position control system

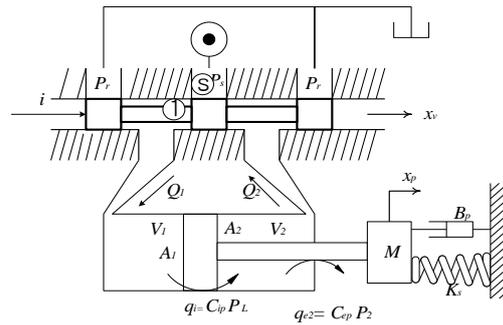


Figure 3: Single-rod electro-hydraulic servo system

Position of the hydraulic cylinder piston is measured with a potentiometer. This information is then fed back to the controller to compute the control input which will generate, via the servo amplifier, the displacement in the servo valve spool so that the position error can be removed by adjusting the flow into the cylinder. Assume that input-current  $i(t)$  and control-input  $u(t)$  has a proportional relation, i.e.,  $i(t) = K_d u(t)$ . The servo valve and the cylinder loading system are shown in Fig.3.

### 2.2 Kinetic equation for the single-rod cylinder

The flow ( $q_1$ ) into the cylinder depending on the spool displacement can be represented by

$$q_1 = Av_1 = C_d wx_v \sqrt{\frac{2(p_s - p_1)}{\rho}} \quad (1)$$

Let the portion supplying flux to the cylinder be defined as the control volume. Applying the law of mass conservation, a kinetic equation in terms of the pressure and the spool depending on the pressure and the spool displacement can be given by Eq. (2):

$$\rho \frac{dV}{dt} + V \frac{d\rho}{dt} = \rho AV \quad (2)$$

Since Eq. (2) is also applicable to the opposite side of the cylinder where the flux flows out, Eq. (3) can be obtained by transforming the density related term into the pressure related one:

$$\begin{aligned} \frac{dV_1}{dt} + \frac{V_1}{K_m} \frac{dp_1}{dt} &= q_1 \\ \frac{dV_2}{dt} + \frac{V_2}{K_m} \frac{dp_2}{dt} &= q_2 \end{aligned} \quad (3)$$

Note that these two equations cannot be combined since a single-rod cylinder is used in this work. Since the spool displacement can be either  $x_v \geq 0$  or  $x_v < 0$ , Eq. (3) is rewritten with regard to the variation of the pressure by introducing a sign function  $\text{sgn}(n)$ :

$$\begin{aligned} \dot{p}_1 &= \frac{K_m}{V_1} (C_d wx_v \text{sgn}(p_s - p_1) \sqrt{\frac{2}{\rho} |p_s - p_1|} - A_1 \dot{x}_p) \\ \dot{p}_2 &= \frac{K_m}{V_2} (C_d wx_v \text{sgn}(p_2 - p_r) \sqrt{\frac{2}{\rho} |p_2 - p_r|} - A_2 \dot{x}_p) \end{aligned}$$

The kinetic equation for the single-rod cylinder and the load can be represented by

$$M \frac{d^2 x_p(t)}{dt^2} + B \frac{dx_p(t)}{dt} + K_s x_p(t) + F_L = (A_1 p_1 - A_2 p_2) \tag{12}$$

Let  $p_1 = x_1, p_2 = x_2, x_p = x_3, \dot{x}_p = x_4$  in Eqs. (1) ~ (5). Ignoring the disturbance  $F_L$  then yields to the state equations in Eq. (6):

$$\begin{aligned} \dot{x}_1 &= \frac{K_m}{V_1} (C_d w x_v \operatorname{sgn}(p_s - p_1) \sqrt{\frac{2}{\rho}} |p_s - x_1| - A_1 x_4) \\ \dot{x}_2 &= \frac{K_m}{V_2} (C_d w x_v \operatorname{sgn}(p_2 - p_r) \sqrt{\frac{2}{\rho}} |x_2 - p_r| - A_2 x_4) \\ \dot{x}_3 &= x_4 \end{aligned} \tag{6}$$

### 3. HYBRID NEURAL-GENETIC ALGORITHM

#### 3.1 Hybrid neural-genetic algorithm

For structured system identification, a large number of algorithms have been developed over the last few decades. The related studies can be referred in [4], [5] and [6]. However, a generic solution to this problem has not been found yet for the system where  $f(\cdot, \cdot)$  and  $g(\cdot, \cdot)$  are nonlinear and  $\theta$  has a higher order.

In this work, a multi-model hybrid neural-genetic algorithm is employed to find unique solutions satisfying with the condition for nonlinear systems identification.

The hybrid neural-genetic algorithm consists of a recurrent incremental credit assignment (ICRA) neural network and a genetic algorithm. The former computes a credit function for each member of a generation of the models while the latter provides the generations of a new model using the credit functions as the selection probabilities. The credit function reflects the closeness of each model's output to the true system output and the genetic algorithm searches the parameter space by a divide-and-conquer technique.

In this paper, every model in a generation is evaluated by using the neural network algorithm, and the generation of a new model is performed by the genetic algorithm in every epochs. In particular, the genetic algorithm is beneficial for searching the globally optimized model.

The ICRA neural network is used to evaluate the model  $Q = (\theta_1, \theta_2, \dots, \theta_K)$ , where  $Q$  contains  $K$ -set of parameters and  $K$  is unknown. The true system output and the model output are given by Eqs. (8) and (9), respectively.

$$Y = \begin{bmatrix} Y_1^k \\ Y_2^k \\ \vdots \\ Y_N^k \end{bmatrix}, \dots, Y_2^k = \begin{bmatrix} y_{N+1} \\ \vdots \\ y_{N+2} \\ \vdots \\ y_{2N} \end{bmatrix} \tag{8}$$

where,  $Y_s^k$  contains the true system output measurements, accumulated over  $N$  time steps, and  $Y_s^k$  contains the output of  $k$ th model, accumulated  $N$  time steps.

Let a new time variable  $S$  be defined such that  $s=1$  for  $t=1, 2, \dots, N$ , and  $s=2$  for,  $t=N+1, N+2, \dots, 2N$  and the error function  $g(\cdot)$  be defined as  $E_s^k$ .

$$E_s^k = Y_s - Y_s^k, \quad g(E_s^k) = e^{-|E_s^k / \sigma|} \tag{10}$$

where  $|\cdot|$  denotes Euclidean norm and  $\sigma$  is a dynamically adjusted error spread parameter. The credit function can be defined as

$$p_s^k = p_{s-1}^k + v \cdot p_{s-1}^k [g(E_s^k) - (\sum_{j=1}^K p_{s-1}^j g(E_s^j))] \tag{11}$$

Eq. (11) is calculated repeatedly with respect to  $s=1, 2, \dots$ , and satisfies Eq. (12) for all  $s$ :

$$0 < p_{s-1}^k \leq 1, \quad \sum_{k=1}^K p_s^k = 1$$

where, the initial values  $p_0^k$  are arbitrarily selected, provided Eq. (12) is satisfied. If  $g(E_s^k)$  is larger than  $g(E_s^j)$ ,  $p_s^k$  determined by Eq. (11) increases. It is important to note that a large  $g(E_s^k)$  implies a small  $E_s^k$ . Hence, the proper value of the credit function indicates how well the  $k$ -th model has approximated the observed model behavior up to time  $s$ . Therefore  $\lim_{s \rightarrow \infty} p_s^k = 1$  indicates a large  $g(E_s^k)$ , which again implies a small  $E_s^k$ . Consequently,  $p_s^k$  which is close to one indicates good approximation and the best model within the parameter space.

Translating the problem of system identification in the genetic algorithm, an individual is a model determined by the parameter vector  $\theta_k$  and the population is search subset  $Q$ . Each parameter is encoded by a string bit, which becomes a concatenation of strings. This concatenation of strings results in a longer string which encodes the parameter  $\theta_k$ . Fitness of each individual is related to the accuracy by which it predicts the system behavior.

#### 3.2 Genetic algorithm composition

The genetic algorithm adopts the following components, which are composed the algorithm.

- 1) Selection Mechanism: A roulette wheel is used to randomly choose the models according to the selection probability which is exactly the ICRA credit.
- 2) Genetic Operation: Mutation operates on a model of the old generation, choosing  $m$  bit out of the  $n \cdot d$  genotype string, and reverses these bits (i.e., 1 becomes 0 and vice verse) Crossover operates on two models of the old generation, dividing the genotype string of each model into  $m$  parts. The offspring is created by choosing the genotype fragment from each parent alternately.
- 3) Elitism: This implies that the best model of each generation is always included in the next generation.
- 4) Entropy criterion: Entropy criterion is used to ensure diversity in the models of each generation. Although Elitism and Hill-climbing can speed up the algorithm, getting into a local minimum rather than a global minimum. To avoid this, in every model generation, it is necessary to maintain a number of models, with sufficient diversity, to be explored. This problem become worse by the elitism and Hill-climbing which tend to enforce the presence of the fitness models. However, if the  $p_s^k$  do not sufficiently concentrate on promising models, the search of the parameter space will be essentially random.

To avoid this problem, the ICRA network must stop operating after the  $p_s^k$ 's start concentrating to a promising model, but before they get too close to either 1 or 0. For achieving this goal, the ICRA neural network has to operate during a variable number of steps. The number of steps is determined depending on an entropy criterion.

$$H_s = - \sum_{k=1}^K p_s^k \cdot \log(p_s^k) \tag{13}$$

The maximum value of  $H_s$  is given by  $\log(K)$ , which is achieved when  $p_s^1 = p_s^2 = p_s^3 = \dots = p_s^K = 1/K$  i.e., the value of  $p_s^k$  is equivalent to every model. The minimum value of  $H_s$  is 0, and is achieved for  $p_s^k = 1, p_s^m = 0, m \neq k$ , i.e., all the probabilities are concentrated on a single model. If the  $p_s^k$  converge to either 0 or 1,  $H_s$  converges to 0. Let the dynamic threshold be defined by Eq. (14)

$$\bar{H}_s : \bar{H}_s = \log(K) \cdot (s/T) \tag{14}$$

Eq.(14) is a linearly increasing function satisfying the inequality Eq. (15) for  $s \leq T$ .

$$H_s < \bar{H}_s$$

$$(15)$$

The inequality Eq. (15) is the entropy criterion which determines a number of varying steps in the ICRA neural network. The ICRA neural network stops operating once the entropy of  $p_s^1, p_s^2, \dots, p_s^K$  becomes lower than  $\bar{H}_s$ . When the  $\bar{H}_s$  is linearly increasing and the  $H_s$  converges to 0, the result stays at a value of entropy between 0 and 1, ensuring the  $p_s^k$  being neither converged nor diverged.

#### 4. Experimental results

##### 4.1 Experimental results

In the experiment, the proposed algorithm is applied to identifying the system parameters including mass, damping coefficient, bulk modulus and spring coefficient. The input-output data set has been obtained from the example electro-hydraulic servo system which is a 1-DOF system. Since the parameters of the example system are unknown, the accuracy of the estimated parameters is evaluated by comparing the estimated trajectories with the measured trajectories. The experimental results have been obtained by applying PRBS as the input to the system described in Fig.1. The sampling time and the number of measured data are 100 Hz and 12000, respectively.

For searching the parameter space, each set of the unknown parameters is defined as an individual of which population size is 30, crossover probability = 0.8, mutation probability = 0.01, and the number of generations = 1000. The ICRA parameter  $\nu=15$  and each generation involves around 500~600 credit updates.

Figure 4 shows the best credit value of each generation. Note that the credit value is converged to the best credit after only 34 generations. Using the Elitism, the best credit has been obtained after 9 generations.

The credit value is given by 0.4008. The identified parameter values are  $M = 58.0$ ,  $C = 3.7$ ,  $K_s = 214.12$ , and  $K_m = 16324.71$ . Note that the identified parameter of  $M$ , which is measurable, is similar to the true value. In Figure 4, only 2000 data are shown to avoid excessive complexity caused by the large data set.

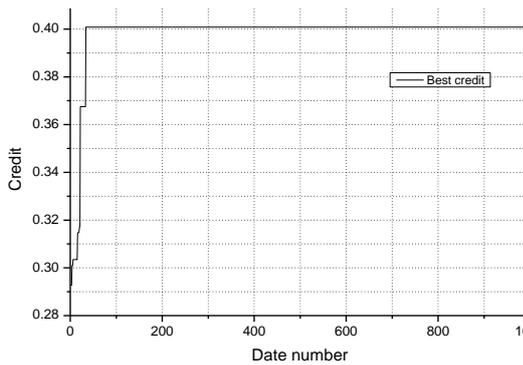


Figure 4: Diagram of best credit in each generation

Figure 5 shows the comparison of the system responses to PRBS. Figure 6 shows the output within the scope of the data 210 ~ 410 in order to assist with clear interpretation.

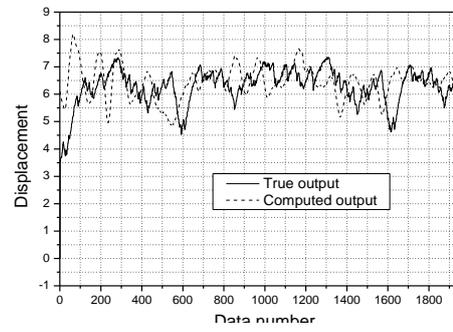


Figure 5: Comparison true output with estimated output

The experimental results in Fig. 5 indicate that there are some discrepancies between the measured and the estimated responses although the overall trend is well matched. The reasons for this error can be the nonlinearities introduced by: directional changes of valve opening; the time delay in the servo valve; friction between the guideline and the bearing; and the noise. These factors have not been considered in the system modeling.

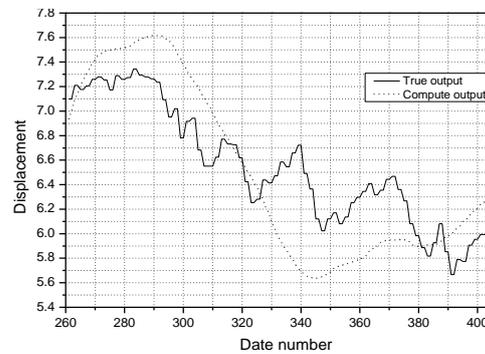


Fig. 6 Detail comparison true output with estimated output in position

Figure 7 illustrates the ISE (integrated square errors) between the responses of the identified model output and the measured output. The reason for not converging to the minimum value is the fact that, once the credit has updated, not only does the ISE converge to the minimum value but also the trend of the actual displacement output is estimated. The experimental results show that the estimation accuracy can be improved if more nonlinearities, such as Coulomb friction, are considered in the system modeling.

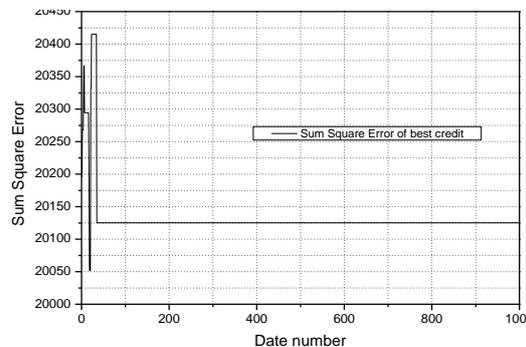


Fig. 7 Squared error in each generation

#### 4.2 Results Discussion

These results highlight that the proposed algorithm is an efficient in

finding the optimal solutions. The accuracy of the parameters identified using the proposed method has also been verified by comparing the estimated results with the measured results.

## 5. Conclusions

In this paper a parameter identification algorithm using a hybrid neural-genetic algorithm has been presented. The proposed algorithm is applied to identifying unknown parameters of an electro-hydraulic servo system. Using a set of input-output data obtained through experiments, several system parameters of the example electro-hydraulic servo system have been identified, which are mass  $M = 58.0$ , damping coefficient  $C = 3.7$ , spring coefficient  $K_s = 214.12$ , and bulk modulus  $K_m = 16324.71$ . These results highlight that the proposed algorithm is efficient in finding the optimal solutions. The accuracy of the parameters identified using the proposed method has also been verified by comparing the estimated results with the measured results. For achieving the better estimation accuracy, it may be necessary to achieve a better resolution as well as to employ a more precise model with an increased number of parameters.

## REFERENCES

1. Navid Niksefat and Nariman Sepehri, "Robust Force Controller Design for an Electro-Hydraulic Actuator Based on Nonlinear Model," Proc. Int. Conf. on robotics & automation, pp. 200-206, 1999.
2. Han-Shue Tan, "Model Identification of an Automotive Hydraulic Active Suspension System," Proc. AACC, pp.2920-2924, 1997.
3. R.Majjad, "Estimation of Suspension Parameters," Proc. IEEE Int. Conf. on control application, pp.522-527, 1997.
4. L. A. Feldkamp, G. V. Puskorius, L.I. Davis,Jr. and F. Yuan, "Neural Control Systems Trained by Dynamic Gradient Methods for Automotive Applications," IEEE Int. Joint Conf. on neural network, vol.2, pp.798-804, 1992.
5. Ahmet Onat, Hajime Kita, Yokohama and Yoshikazu Nishikawa, "Recurrent neural networks for Reinforcement Learning: Architecture, Learning Algorithms and Internal Representation," IEEE Int. Conf. on neural network, vol.3, pp.2010-2015, 1998.
6. Ahmed Rubaai and Raj Kotaru, "Adaptation Learning Control Scheme a High Performance Permanent Magnet Stepper Motor Using Online Random Training of Neural Networks," IEEE Trans. on industry applications, vol.37, no.2, 2001.
7. Vassilios Petridis, Emmanuel Paterakis and Athanasios Kehagiaas, "A Hybrid Neural Genetic Multimodel Parameter Estimation Algorithm," IEEE Trans. on neural networks, vol.9, No.5, pp862-876, 1998.