IDENTIFICATION OF A POPPET VALVE USING GENETIC PROGRAMMING METHOD BASED ON ADAPTIVE PROBABILITIES WITH CHAOTIC TUNING AND ORTHOGONAL LEAST SQUARES

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Abstract. *Most processes in industry are characterized by nonlinear and time-varying behavior. In this context, the identification of mathematical models, typically nonlinear systems, is vital in many fields of engineering. A variety of system identification techniques are applied to model the processes dynamic. Recently, the identification of nonlinear systems by genetic programming (GP) approaches has been successfully applied in many applications. GP is a paradigm of evolutionary computation field based on a structure description method that applies the principles of natural evolution to optimization problems and its nature is a generalized hierarchy computer program description. GP adopts a tree structure code to describe an identification problem. Unlike the traditional approximation methods where the structure of an approximated model is fixed, the structure of the GP tree itself is modified and optimized and, thus, there is a possibility that GP trees could be more appropriate or accurate approximating models. This paper proposed a GP method combined with an orthogonal least squares (OLS) algorithm to estimate the contribution of the tree branches to the accuracy of the discrete polynomial NARX (Nonlinear AutoRegressive with eXogenous inputs) model. The nonlinear system identification procedure, based on a NARX representation and a GP optimization approach built on adaptive probabilities using chaotic sequences, is applied to the case study of an experimental poppet valve. Poppet valves are normally used in combustion engines to open and close the intake and exhaust ports on the cylinder head. The very well machined adjust between seat and poppet gives the sealing feature that is improved every time that the pressure inside the cylinder rises up pushing the valve head against its seat. The modeled device controls the amount of recirculated gases and it is used in the automotive industry to control the emissions levels on combustion engines. The identification results demonstrate that the GP with OLS is a promising technique for NARX modeling.*

Keywords*: nonlinear identification, poppet valves, genetic programming, NARX modeling.*

1. INTRODUCTION

Developing models from observed data, or function learning, is a fundamental problem in engineering systems, such as control systems, supervision approaches and prediction methods. System identification is the procedure of constructing a mathematical model from input-output data for a dynamic system under testing and characterizing the system behaviors. The identification of dynamic nonlinear systems, which pose problems and require solutions distinct from their linear counterparts, is a hard task as demonstrated by the effort devoted by researchers in the last decades. Several techniques have been proposed for nonlinear system identification (Giannais and Serpedin, 2001; Billings, 1980; Ljung, 2001; Haber and Unbehauen, 1990).

In recent years, genetic programming (GP) (Lew *et al*., 2006; Beliagiannis *et al*., 2005; Yang, 2006; Zhang and Nandi, 2007), a member of the evolutionary computation field, has been applied to fault detection, modeling and identification of nonlinear systems. GP is a stochastic process for automatically generating computer programs and was introduced by Koza (1992), based on the idea of genetic algorithms. An advantage of GP is that it can evolve a solution automatically from the training data and does not require an assumption regarding the mathematical model, on the model's structure or size of the decision tree-based solution.

This paper investigates a GP method based on tuning procedure of crossover and mutation probabilities and an orthogonal least squares (OLS) algorithm to estimate the contribution of the branches of the tree to the accuracy of the discrete polynomial NARX (Nonlinear AutoRegressive with eXogenous inputs) model. The identification procedure using GP based on OLS for NARX nonlinear identification validated in this paper was inspired in Mádar *et al*. (2005) including the tuning procedure of crossover and mutation probabilities.

To illustrate the power of the proposed GP methodology in NARX identification, the experimental data obtained of a poppet valve is considered. Poppet valves are normally used in combustion engines to open and close the intake and exhaust ports in the cylinder head. The very well machined adjust between seat and poppet gives the sealing feature that is improved every time that the pressure inside the cylinder rises up pushing the valve head against its seat. In this work, a poppet valve, driven by an electrical motor is evaluated. This device is used in the automotive industry to control the emissions levels on combustion engines by controlling the gases recirculated.

The remainder of this paper is organized as follows. In Section 2, the fundamentals of system identification are presented. The theoretical background of GP method is introduced in Section 3. Description of case study of a poppet valve and the identification results are both commented in Section 4. Finally, the conclusion and further research are discussed in Section 5.

2. FUNDAMENTALS OF SYSTEM IDENTIFICATION

Inferring mathematical models of dynamical systems from laboratory or field observations has always been a subject of interest in science and engineering. An important subdivision of this field addresses the identification of nonlinear systems, which pose problems and require solutions distinct from their linear counterparts. For linear system identification (Ljung, 1999; Schoukens and Pintelon, 1991), unique solutions normally exist for over determined problems where there are more equations than the unknown parameters and the error distribution of the extracted parameters usually can be calculated from the measured error.

The linear mathematical model is useful if the underlying physical process exhibits qualitatively similar dynamic behavior to the linear model in the operating point of interest. However, it is often difficult to represent the behavior of the system on its full range of operation using linear mathematical models. For these reasons, there is current research interest in models for nonlinear identification. In this context, many system modeling and parameter identification techniques have been successfully proposed (see Giannais and Serpedin, 2001).

Due to the nonlinear nature of many systems, this paper investigates a GP method combined with OLS algorithm to NARX modeling. In this context, the model identification adopted is summarized by the following steps:

Step i) design an experiment to obtain the process input/output data sets pertinent to the model application

Step ii) examine the quality of measured data, removing trends and outliers.

Step iii) construct a set of candidate models based on information from the experimental data sets (or simulation data sets). This step is the model structure identification.

Step iv) select a particular model from the set of candidate models and estimate the model parameter values using the experimental data sets (or simulation data sets).

Step v) evaluate how good the model is using a performance criterion.

Step vi) if a satisfactory model is still not obtained in Step v then repeat the procedure either for Step i or Step iii, depending on the problem.

3. GENETIC PROGRAMMING

Evolutionary Algorithms (EAs) are powerful tools used for solving difficult real-world problems. They have been developed in order to solve some problems that the classical (mathematical) methods failed to successfully tackle. Many of these unsolved problems are (or could be turned into) optimization problems. The solving of an optimization problem means finding solutions that maximize or minimize one or more criteria function (Goldberg, 1989). GP is an EA that produces functional programs to solve a given task. GP, introduced by Koza and his group (Koza, 1992; Koza, 1999; Koza, 2003), is popular for its ability to learn hidden relationships in data and express them automatically in a mathematical manner. GP has already spawned numerous interesting applications.

In the GP paradigm, problems in systems identification field are viewed as the discovery of computer programs through a search process (global optimization) based on the rules of natural selection and natural genetics. Due to its population-based nature, GP approaches can avoid being trapped in a local optimum and consequently have the ability to find global suitable solutions.

In GP, solutions to a problem can be represented in different forms, but are usually interpreted as computer programs. The computer programs represent candidate solutions to a problem. The typical structure of each individual can be seen as a tree-shaped structure to represent the individuals in the evolving population. Each candidate solution or individual of which has a fitness.

The mentioned trees are typically encoded as *S*-expressions, the syntactic form in Lisp (LISt Processing language) programming language and the basic units of trees are called nodes. The GP procedure employs usually a context-free grammar declared in *Backus-Naur-Form* (BNF). The BNF-grammar consists of non-terminal nodes and terminal nodes and is represented by the set {*N*, *T*, *P*, *S*}, where *N* is the set of non-terminals (function set), *T* is the set of terminals, *P* is the set of production rules and *S* is a member of *N* corresponding to the starting symbol [33].

The leaf nodes are input variables from the *terminal set T*, and internal nodes are operators from the *function set F*. Each candidate solution is built from combining all possible functions and terminals. The function set is the operators and functions such as arithmetic operators of addition, subtraction, multiplication, and division as well as a conditional branching operator.

In general terms, the steps of a classical genetic programming approach can be summarized in the following steps:

Step i) *Initialization of candidate solutions*: An initial population with candidate solutions (individuals) is generated.

Step ii) *Selection*: The individuals that performed better in the evaluation process have more possibilities of being selected as parents for the new population than the rest. Tournament selection is adopted in order to select two parents. According to this strategy, two individuals among the current population are randomly selected, and the one with higher fitness win the right to mate. The process is repeated for the other parent.

Step iii) *Crossover*: Two randomly chosen sub-trees of the two selected parents are exchanged to create two offspring. The crossover rate is p_c.

Step iv) *Mutation*: N_m duplicates of each offspring are created, and their terminal nodes mutate by replacing the original values with the neighbor values randomly selected from the component value set. The crossover rate is p_m.

Step v) *Replacement*: The fitness of the original offspring and their mutated versions are calculated to pick up the fittest one, which should replace the worst individual of the current population if the former is fitter than the latter.

Step vi) *Termination Criteria*: If a maximum number of iterations, t_{max}, is reached, the process stops; otherwise, go to Step ii.

The performance of GP is sensitive to the choice of control parameters. Choosing suitable parameter values is, frequently, a problem dependent task and requires previous user experience. Proper control parameters are recommended to some certain values to provide the algorithm better performance from the two aspects of effectiveness and efficiency according to the computational experiments. Despite its crucial importance, there is no consistent methodology for determining the control parameters of an EA, which are, most of the time, arbitrarily set within some predefined ranges (Eiben *et al*., 1999).

Two major forms of setting parameter values must be mentioned: parameter *tuning* and parameter *control* (Eiben *et al*., 1999). The former means the commonly practiced approach that tries to find good values for the parameters before running the algorithm, then tuning the algorithm using these values, which remain fixed during the run. The latter means that values for the parameters are changed during the run.

In this paper, an adaptive setting of control parameters of crossover and mutation probabilities based on chaotic sequences in GP is provided. The application of chaotic sequences instead of random sequences in GP is an alternative strategy to diversify the population and improve the GP's performance and other evolutionary algorithms in preventing premature convergence to local minima. One of the simplest dynamic systems evidencing chaotic behavior is the iterator called the logistic map (May, 1976), whose equation is given by:

$$z(t) = \mu \cdot z(t-1) \cdot [1 - z(t-1)] \quad (1)$$

where t is the sample, and μ is a control parameter, $0 \le \mu \le 4$. The behavior of the system of equation (5) is greatly changed with the variation of μ. The value of μ determines whether z stabilizes at a constant size, oscillates between a limited sequence of sizes or behaves chaotically in an unpredictable pattern. A very small difference in the initial value of z causes substantial differences in its long-time behavior. Equation (1) is deterministic, displaying chaotic dynamics when $\mu = 4$ and $z(1) \notin \{0, 0.25, 0.50, 0.75, 1\}$ (Coelho and Mariani, 2006). In this case, $x(t)$ is distributed in the range (0,1) providing the initial $z(1) \in (0,1)$ and $z(1) = 0.48$, as was adopted here. In this case, the values of p_c and p_m in GP method based on chaotic sequences (CHGP) are modified using the equation (1).

3.1. GENETIC PROGRAMMING FOR NARX IDENTIFICATION

The GP can optimize both the model structure as well as its parameters in applications of identification mainly nonlinear identification. Among this class of models, the identification of discrete-time, NARX (nonlinear ARX) is considered in this paper. In the NARX model, the model regressors are input $u(k)$ and output $y(k)$ observations for the discrete time k. The NARX model is given by:

$$y(k) = f(y(k-1),...,y(k-n_y),u(k-t_d-1),u(k-t_d-2),...,u(k-t_d-n_u)) + e(k), \quad (2)$$

where $y(k)$ is system output for the time k, f is an unknown static nonlinear mapping, t_d is the delay time (dead time), n_u and n_y are the maximum and output lags (often referred to as model orders), respectively, while $e(k)$ represents the modeling error and is assumed to be Gaussian noise. The above SISO (Single-Input Single Output) system representation can be assumed without a loss of generality since the extension to MISO (Multiple-Input Single-Output) and MIMO (Multiple-Input Multiple-Output) systems is straightforward.

Letting $\hat{y}(k) = f(y(k-1),...,y(k-n_y),u(k-d),u(k-d-1),...,u(k-d-n_u))$, where $\hat{y}(k)$ is predicted output for the time k, the NARX identification problem amounts to reconstructing the nonlinear mapping $f(\cdot)$: $\Re^{\beta} \rightarrow \Re$, $\beta = n_u + n_y$ form the set ($y(k)$, $u(k)$), k = 1, 2,…, n (Nicolao and Trecate, 1999). Since the mentioned set provides a non-uniform and incomplete sampling of the domain of f, a generalization problem arises than can e solved by resorting to GP.

Linear-in-parameters mathematical models can be formulated as:

$$y(k) = \sum_{i=1}^{M} p_i \cdot F_i\left(x(k)\right) \quad (3)$$

where F_1, ..., F_M are nonlinear functions (they do not contain parameters), $x(k)$ is the regressor vector that consists of lagged input(s) and output(s) given by $x(k) = [y(k-1),...,y(k-n_y),u(k-d),u(k-d-1),...,u(k-d-n_u)]$, and p_1, ..., p_M are model parameters (Mádar *et al*., 2005). The problem of model structure selection for linear-in-parameters models is to find the proper set of nonlinear functions.

There are a vast number of possible structures; hence, in practice, it is impossible to evaluate all of them. Even if the set of possible structures is restricted only to polynomial models given by (Mádar *et al*., 2005):

$$y(k) = p_0 + \sum_{i_1=1}^{m} p_{i_1} \cdot x_{i_1}(k) + \sum_{i_1=1}^{m}\sum_{i_2=i_1}^{m} p_{i_1 i_2} \cdot x_{i_1}(k) \cdot x_{i_2}(k) + ... + \sum_{i_1=1}^{m} ... \sum_{i_d=i_{d-1}} p_{i_1,...,i_d} \prod_{j=1}^{m} x_{i_j}(k) \quad (4)$$

where p_0 is a constant term. The construction of a NARX model consists of the selection of many structural parameters, which have significant effect to the performance of the designed model.

The number of parameters (number of polynomial terms) is given by (Mádar *et al*., 2005):

$$n_p = \frac{(d+m)!}{d!m!}. \quad (5)$$

Analytical resolution of parameter estimation problem of NARX is a complex task. The GP method combined with the OLS for the structure selection of NARX models that are linear-in-parameters is addressed in this context. Generally, GP creates nonlinear models in addition to linear-in-parameters models. To avoid nonlinear-in-parameters models, the parameters must be removed from the set of terminals; i.e., it contains only variables: $T = \{x_1(k), ..., x_m(k)\}$, where $x_i(k)$ denotes the ith regressor variable. During the operation of GP, the algorithm generates many potential solutions in the form of a tree structure. These trees may have terms (sub-trees) that contribute more or less to the accuracy of the model. In this context, the parameters are assigned to the model after "extraction" of the F_i function terms from the tree, and they are determined using the OLS (Korenberg *et al*., 1998) algorithm with the error reduction ratio (ERR) measure.

4. DESCRIPTION OF CASE STUDY AND IDENTIFICATION RESULTS USING GP APPROACHES

In this section, it turns to the description of poppet valve and analysis of the results obtained by the GP and CHGP approaches.

4.1. System description

In this work a device, called poppet valve, driven by an electrical motor is identified. Figure 1 shows the valve components and to ease the explanation the whole valve is split in: i) mechanism, ii) sensor, and iii) electrical motor. These components, details of signals acquisition, and setup of GP approaches for identification of poppet valve are described in the next subsections.

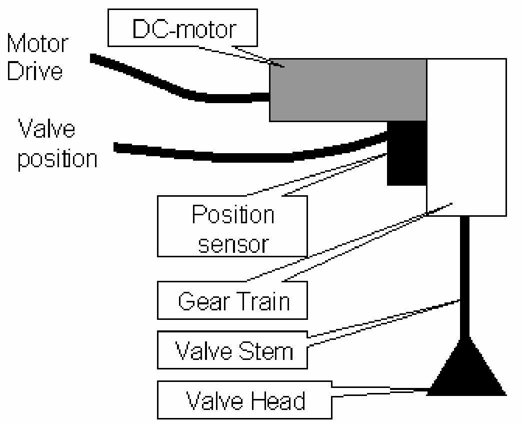

Figure 1. Components of the poppet valve.

4.1.1. Valve mechanism

The object valve concept is based on a poppet valve acted by gear train and an electric motor. The electric motor is attached to the first rotary axle and the latest rotary axle has a position sensor coupled. The gear train transforms the rotary movement into a linear movement by using a link that is similar to a connection rod. Figure 2 shows the valve mechanism sketch:

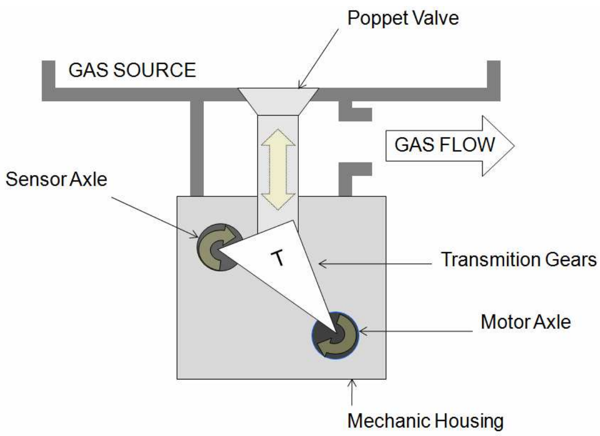

Figure 2. Diagram of valve sketch.

Maximum power and speed action will be set by the gear train ratio and by the motor construction. The gas source is sealed by a conic poppet that moves linearly. The gas flow trough the valve is set by the cone angle, head diameter, cylindrical stem diameter and the poppet position related to the valve seat. Figure 3 shows the valve with full flow:

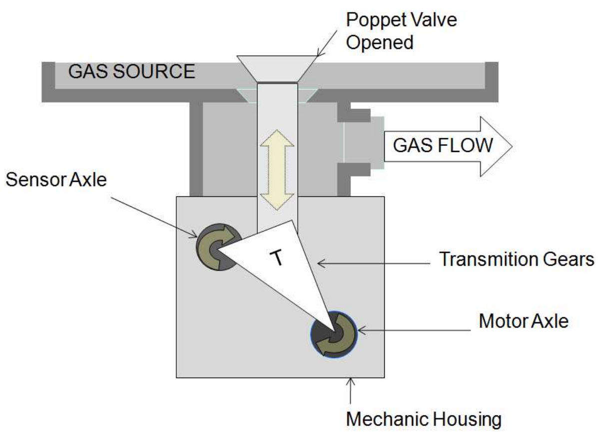

Figure 3. Valve full flow.

4.1.2. Sensor

The valve design has a position sensor coupled to the latest rotary axle in the gear train. This kind of assembly is used to avoid that the mechanical clearance, needed to a correct gear coupling, affects the control system. The applied sensor is a hall-effect sensor, based on magnetic field properties. A correct coupling is achieved when the valve travel is totally proportional to the sensor voltage. In order to check the coupling in real valves four new valve samples were tested. The applied method followed the steps: i) the valve is requested to be in ten percent of its total travel; ii) poppet absolute position is measured using a mechanical gauge and sensor feedback voltage is taken with a multimeter; iii) the requested position is increased by ten percent and the last steps (ii) is performed again (forward operation); iv) the steps ii and iii are repeated until the valve reaches full travel; and v) all the steps are repeated for backward operation.

All gathered data build up a table and the average was plot in a graph. Figure 4 shows the average values for sensor voltage and valve travel according to the requested position. In the Figure 4, two set of curves are presented. Upper curves are related to the sensor voltage. They show a little offset among the acquired values that is probably related to the sensor production tolerances. Lower curves are related to the valve travel and they show great linearity and also repeatability among the tested objects.

The travel and the sensor correlation clarify that any control system used in this device should deal with a small non-proportionality between the signals. A control applied to this valve should also foresee a small difference between the forward and backward operation due lifetime against the increase of clearance caused by the normal friction during the gear engagement.

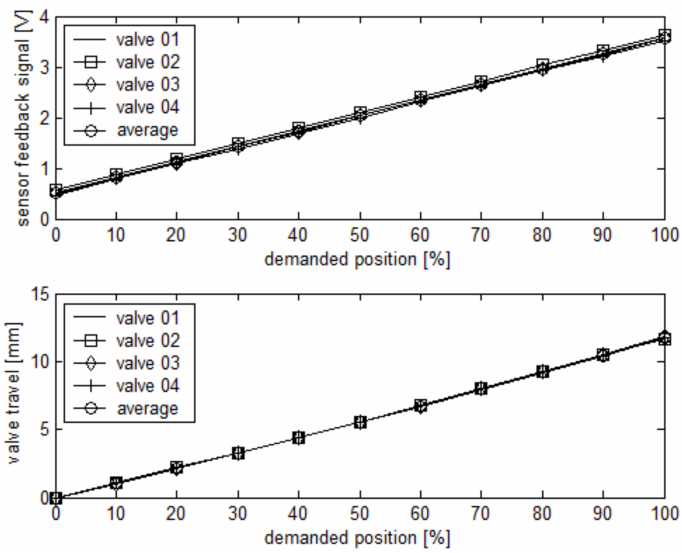

Figure 4. Valve travel and sensor voltage.

4.1.3. Electrical motor

The electric motor is a common DC type with carbon brushes, driven by a PWM (Pulse Width Modulation) module in order to control the power and consequently the position forward or backward.

To assure the correct system tuning is needed a better understanding on the motor behavior and its limits. A test took place in order to plot the motor power curve. A load cell (from 0 up to 3 KN) was used to determine the motor power. It was attached to the end of the poppet and the valve body was hold in the opposite side by a bracket leaving the poppet approximately 5 mm opened. The motor current was increased from 0 up to 3 Ampere and the strength measured by the load cell was recorded each 0.2 Ampere. There were tested three new valves and two used ones. The test room had the temperature stable on 20 ºC during the whole test procedure. The acquired value are presented in Figure 5.

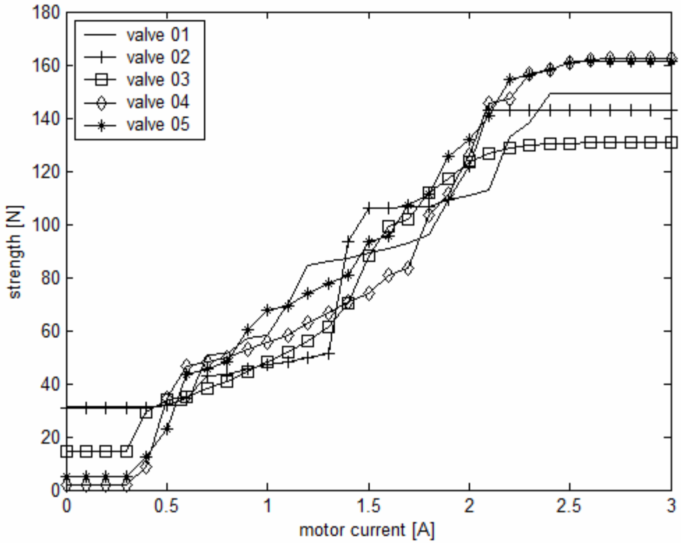

Figure 5. Motor power curve.

Analyzing the Figure 5, one can conclude that the saturation current is among 2.3 A. Despite the fact that the start power was a bit different among all test samples, the middle curve presents small differences between the different test objects.

In the next subsections, the valve testing in open and closed-loop responses are presented and commented.

4.2. Valve testing

Some tests were performed to detect the system behavior and further model it.

Open-Loop Step Response: The step response was recorded in an open-loop condition by supplying the motor with a Direct Current (DC) constant voltage and acquiring the feedback sensor signal. Figure 6 shows the open loop step response. It is clear that in an open loop condition the valve shown a dead time and afterwards a linear response.

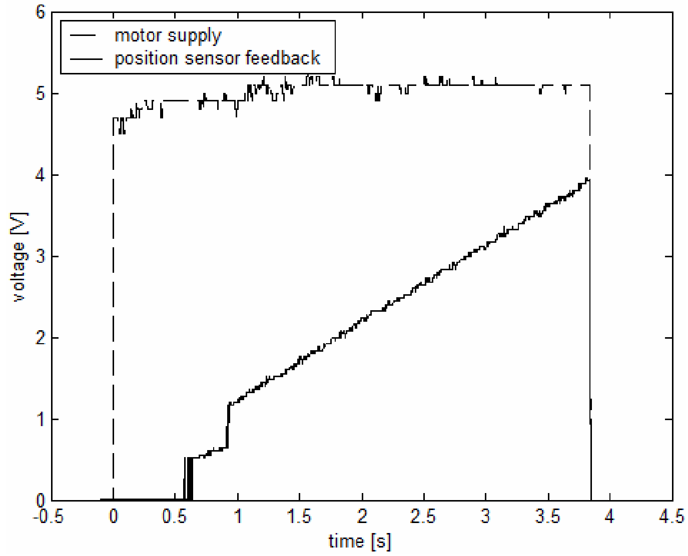

Figure 6. Open-loop step response.

Closed-Loop Step Response: A closed loop acquisition was also performed using a proportional-integral (PI) controller with an anti-windup function and gain over the position error equal to 197.6. To decrease the measuring problems five brand new and six used valves were tested with the same procedure. An input step requesting 100% of the valve travel was made then the position feedback and current response were recorded.

Figure 7 shows the curve for every tested valve regarding the position feedback and motor current consumption after the input step. Most of the valves had almost the same positioning behavior except two valves those had a position increasing much more linear than the other valves. It is possible to conclude that every valve asked a similar current pattern for the movement and the current level depended on the valve life. Used valves needed more current to make the same movement as expected. The maximum continuous current for all samples stayed lower than ± 2.3 A that was pointed out as current saturation (see Figure 5).

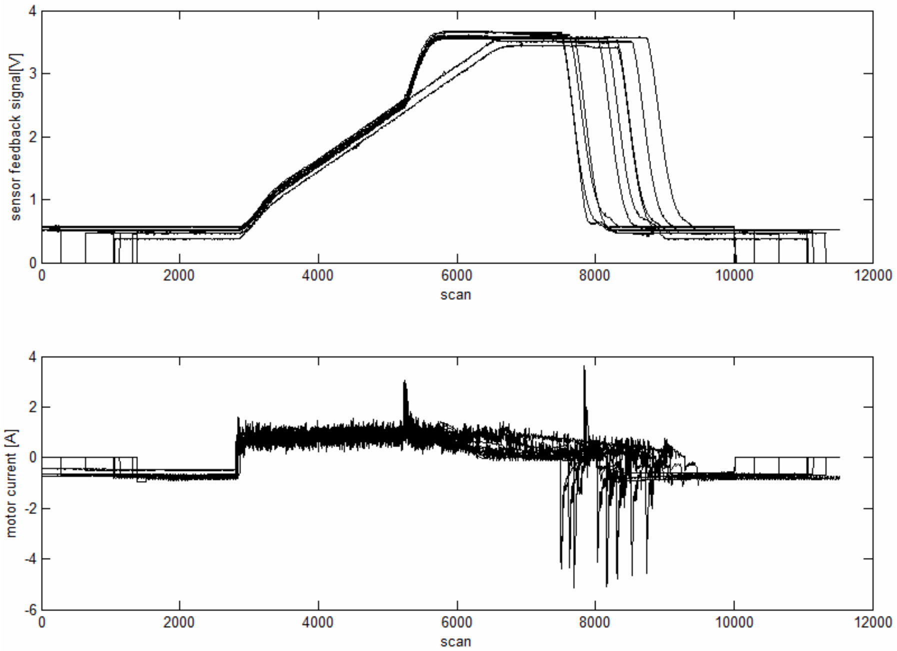

Figure 7. Closed-loop data.

4.3. Data for system identification

In order to avoid the control interferences on the system identification all the gains were made unitary and the integral action was disabled. The PRBS (Pseudorandom Binary Sequence) was chosen as input signal. Figure 8 presents the input and output signals for this data acquisition. These signals are used in identification procedure based on GP and CHGP approaches.

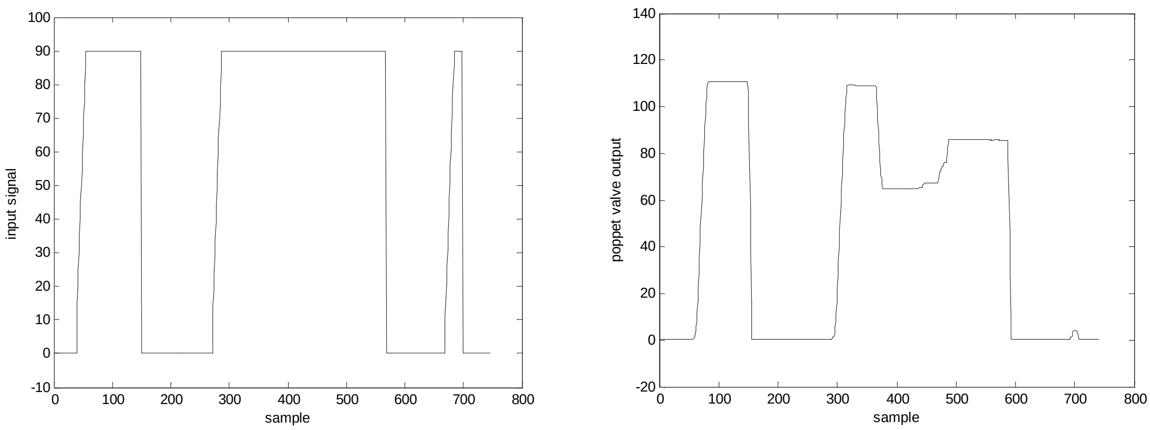

Figure 8. PRBS response.

GP and CHGP approaches were implemented in MATLAB (MathWorks). All the programs were run under a Pentium dual-core processor with 1.73 GHz and 2 GB of Random Access Memory (RAM). In order to eliminate stochastic discrepancy, in each case study, 30 independent runs were made for each of the optimization methods involving 30 different initial trial solutions for the GP and CHGP approach.

The parameters of the GP approaches are set as follows: population size is 30, generation gap = 0.8, selection adopted is the tournament with elitist strategy, the tournament size is equal to 6, the maximum number of generations is 200, and the maximum allowed tree depth is 5. The design parameter adopted for the OLS algorithm is ERR = 0.01.

The system identification by NARX model based on GP is appropriate if a performance index is in values permissible for the user's needs. In this case, the fitness function for maximization proposes is given by the multiple correlation index (also known as the *R*-squared coefficient) for the estimation (optimization) phase (R_{est}^2 value) and validation (test) phase (R_{val}^2 value). When the value R^2 =1.0 (estimation or validation phases), it indicates the model's accurate approach to the system's measured data. A R^2 value between 0.9 and 1.0 is considered sufficient for applications in identification and model-based controller design (Schaible *et al.*, 1997).

The first 400 samples of poppet valve system are used for the estimation phase, while the remaining 345 samples are used for the validation phase. The maximum input and output order selected for identification with GP and CHGP are t_d =1, n_u = 4, and n_y = 4. All of the numeric parameters in GP approaches design are determined empirically.

The equation with best R^2_{est} (R^2_{est} = 0.9996) for the NARX model obtained by CHGP approach in 30 runs was

$$y(k) = 0.098800 + 1.191029 \cdot y(k-1) - 1.563875 \cdot y(k-2) + 0.355320 \cdot y(k-3) + 0.000185 \cdot y(k-1) \cdot u(k-4) \quad (6)$$

The model of equation (6) presents an error mean to 745 samples equal to 0.0139 and R^2_{est} = 0.9995. On other hand, the best model obtained by GP in 30 runs presented R^2_{est} = 0.9991. It can conclude that a best solution found by CHGP has a slight advantage over the result of GP. The best result of CHGP approach for the poppet valve is showed in Figure 9.

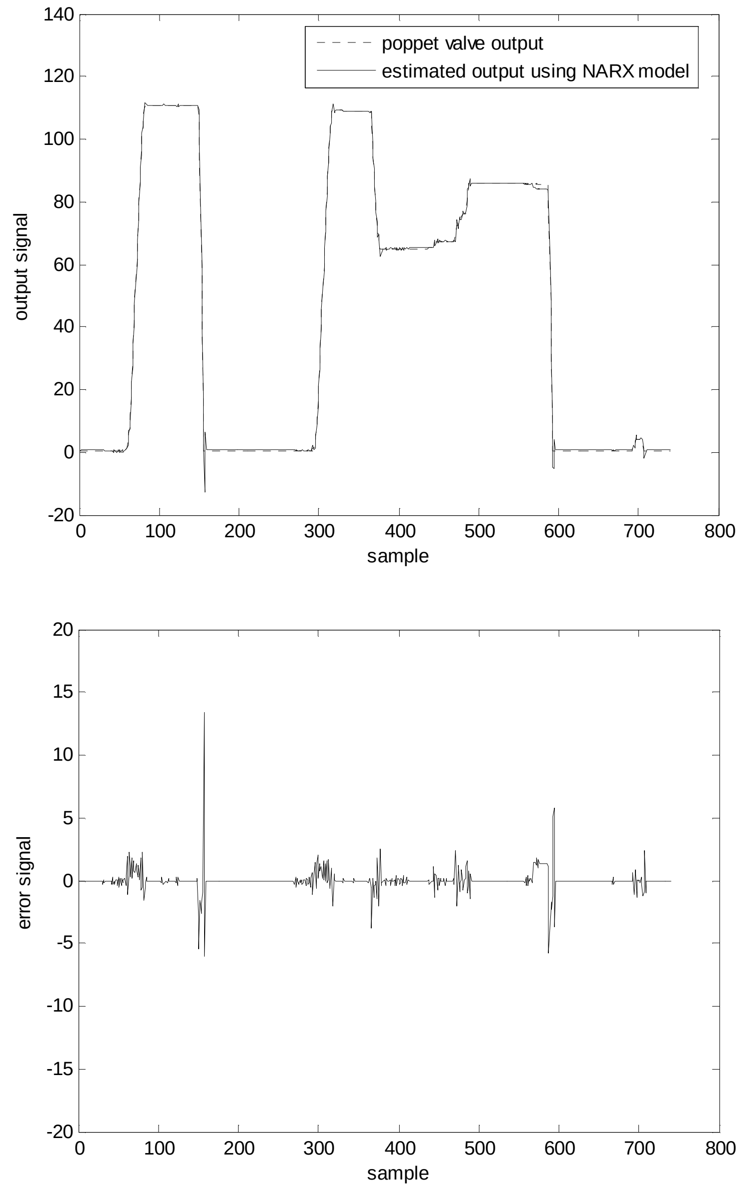

Figure 9. Best result of R^2_{est} for NARX modeling obtained by CHGP.

5. CONCLUSION AND FUTURE RESEARCH

This paper focuses the application of two GP approaches combined with OLS algorithm for structure selection of a NARX model. The identification procedure based on GP and CHGP approaches and NARX model was validated to identify a poppet valve system. Results demonstrated that the CHGP method is a consistent estimator when applied to identification of NARX models.

Future research is to investigate the performance of GP and CHGP approaches for solving optimization problems in model-based controllers design.

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