Parameter estimation using genetic algorithm technique

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Abstract: A system identification problem can be formulated as an optimization task where the objective is to find a model and a set of parameters that minimize the prediction error between the plant output (the measured data) and the model output. The most existing system identification approaches are highly analytical and based on mathematical derivation of the system's model. As an alternative to these methods, evolutionary computation such as Genetic Algorithm (GA) seems to be a very capable approach, because it needs only little knowledge about the problem to be solved. This paper presents a system identification technique based on an evolutionary strategy. The GA approach has shown to be versatile when applied to parameters estimation without requiring a detailed mathematical representation. and attempts to show how genetic algorithm (GA) can be applied in system identification tasks as off line identification of the Ball and Hoop system as the case study of this work. The least square was used to compare and contrast the intelligent identification techniques with adaptive techniques.

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1. Introduction

The area of system identification has received a lot of attention over the last four decades. It is now a fairly mature field, and many powerful methods are at the disposal of control engineers [1]. System identification consists of two tasks. The first task is structural identification of the equations and the second one is an estimation of the model's parameters. In control engineering, system identification is used to find a model of the plant to control. In this context, system models describe the behavior of the plant over time [2]. In the case of the structure the model is known in advance, the needed knowledge relies to the numerical values of a number of parameters. In this paper the investigational estimation of parameters will be referred. These methods use the measurements carried out on input and output signals, having the goal to find the mathematical model, very close to reality and the behavior of the plant. There are many search methods which have been developed and applied to structural identification. Identification methods may be classified into two groups, traditional and intelligent techniques. Traditional methods have many drawbacks such as requiring a good initial guess, being sensitive to noise and converging often to local optima such as least square and instrumental variable method. With the increases in available computational speed, intelligent techniques are becoming more popular, such as genetic algorithms, genetic programming. The genetic algorithm (GA) is a parallel, global search technique that emulates natural genetic operators. Because it simultaneously evaluates many points in the search space, it is more likely to converge toward the global solution [3].

2. System identification

System identification deals with the problem of building mathematical models based on observed data from the system. Mathematical models are used for different purposes in different disciplines [4]. In engineering, for example, models are used for the analysis of an existing process; prediction of the behavior of certain system; control design; simulation; and fault detection. Figure1 illustrates the task of system identification, where the simulated output of a model $\hat{y}(t)$ is compared with the measured output of a system $y(t)$, which is corrupted by noise (n), and an error signal $e(t)$ is generated to adapt the model [5].

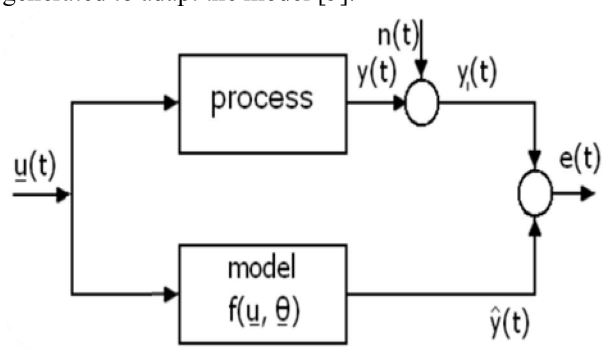

Figure 1. System identification task

3. Parameter estimation

Parameter estimation is of primary importance in many areas of process modeling. The objective of Parameter estimation is to determine values of model parameters that provide the best fit to measured data. If the structural form of the describing differential equation is known, then the unknown parameters can be estimated using the well known least square methods [6]. The process parameter estimation is a part of system identification. In a broader sense, system identification is selection of model structure, experiment design, parameter estimation, and validation data.

3.1. Least Squares Parameter Estimation

The least-square method is commonly used in system identification. Its principle is that the unknown parameters of a mathematical model should be chosen by minimizing the sum of the square of the difference between the actually observed and the analytically predicted output values with possible weighting that measure the degree of precision [4].

3.2. Results for Least Squares

The ball and hoop system is identified and the transfer function is obtained in equation (1) [7]-[8].

$$H(s)=\frac{30.051s^2+134.0132s}{0.9372s^4+2.656s^3+75.87s^2+112.1s} \tag{1}$$

The discrete transfer function is:

$$H(z)=\frac{y(z)}{u(z)}=\frac{0.04046\,z^2+0.009158\,z-0.03323}{z^3-2.675\,z^2+2.557\,z-0.8679} \tag{2}$$

and the system with unknown parameter can be represented by relation.

$$H(z)=\frac{y(z)}{u(z)}=\frac{a_1z^2+a_2z-a_3}{z^3-b_1z^2+b_2z-b_3} \tag{3}$$

Using the same pseudo random binary sequence (PRBS) as the input signal and adding the effect of noise (zero-mean white noise sequence) with standard deviation (0.002).

The component of estimated parameters after 500 pair of data is shown in Table (1):

Table (1): system parameters after (500) sample

Parameter	Estimated parameter values
a1	0.0397
a2	0.0136
a3	-0.0299
b1	-2.5822
b2	2. 3929
b3	-0.7807

There for the estimated model of the system becomes:

$$H(z)=\frac{y(z)}{u(z)}=\frac{0.0397z^2+0.0136z-0.0299}{z^3-2.5822z^2+2.3929z-0.7807} \tag{4}$$

The parameters of system which corrupted by noise is not converging to the actual values; LS cannot model the ball and hoop system. And the step response of plant model versus estimated model is shown in figure 2.

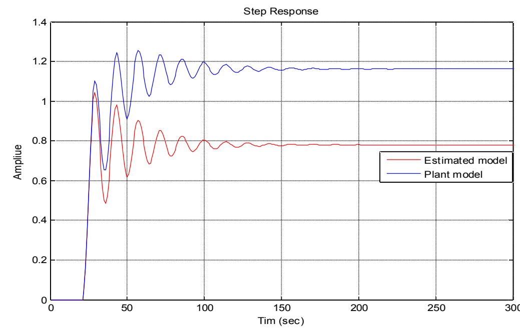

Figure 2. step response of plant model versus estimated model (500 data points)

4. Genetic Algorithm (GA)

GA is a powerful search technique that imitates the process of natural evolution. The main idea behind GA that it can do what nature does.

The GA starts with no knowledge of the correct solution and depends entirely on responses from its environment and evolution operators (i.e. reproduction, crossover and mutation) to reach the best solution. By starting at several independent points and searching in parallel, the algorithm avoids local minima and converging to sub optimal solutions. In this way, GA has been shown to be capable of locating high performance areas in complex domains without experiencing the difficulties associated with high dimensionality, as may occur with gradient decent techniques or methods that depends on derivative information [9].

In order for genetic algorithm to surpass their more traditional techniques in the quest for robustness, they must differ from more normal optimization and search procedures in four fundamental ways:

- GA searches a population of points in parallel rather than a single point.
- GA uses probabilistic transition rules, not deterministic rules.
- GA uses information only from the objective function, they do not require derivatives or other auxiliary knowledge.
- GA works with an encoding of the parameter set, not the parameters themselves.

A genetic algorithm is typically initialized with a random population consisting of between 20-100 individuals. This population (mating pool) is usually represented by a real-valued number or a binary string called a chromosome. For illustrative purposes, the rest of this section represents each chromosome as a binary string. How well an individual performs a task which measured by the objective function. The objective function assigns each individual a corresponding number called its fitness. The fitness of each chromosome is assessed and a survival of the fittest strategy is applied [8].

5. Proposed Methods for Parameter Estimation

The phases to be passed for proposed parameters estimation are obtainable in Figure3. The described method uses as starting point an approximate plant model. The model's outputs are compared with the actual output and an error criteria associated to the plant outputs and the mathematical model outputs is used. The mathematical model's those parameters are determined which lead to an output that fits the best to the Plant outputs carried out by experimental measurements. These stages are then continued until the error criterion is met. [2]

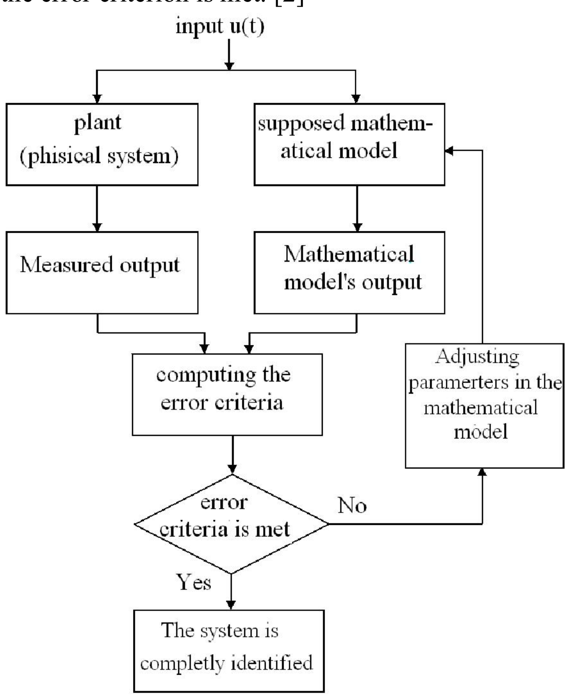

Figure 3. The proposed parameters estimation phases

The identification can be carried out on-line or off-line. In the on-line case, the input and output signals used are those, which appear in the usual operation of the plant and the model of the system is obtained in real time.

In the off-line case, also the signals that appear in the usual operation of the plant are employed, but these signals are previously collected [2]- [7].

6. Modeling using genetic algorithm

The bloc Model has adjustable parameters, which are transmitted from GA in the evaluation step. By comparing the y (t) and ym (t) outputs, a measure of the performance is obtained, on base of which the individual has assigned the Fitness function [1].

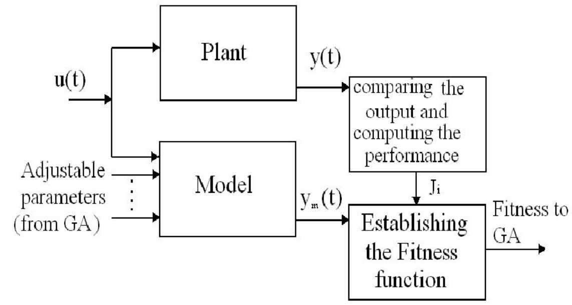

Figure (4) the principle scheme for parameters estimation

The total summation of square error (SSE) is taken as an objective function, which is given by relation:

$$SSE = \frac{1}{2}\sum_{t=1}^{n}\left(y(t) - y_m(t)\right)^2 = \frac{1}{2}\sum_{t=1}^{n} e^2(t) \qquad (5)$$

Where " t "the number of is given sampling steps, y_m is the evaluated output from GA, and "e" is the error between y and y_m. The objective is to determine the system parameters based on using the proposed GA in such a way that the value of SSE in equation(5) is minimized, approaching zero as much as possible. The first step is to generate input signal, then collect the output data of the system. In this study, the (PRBS) used as genetic identification input; the input/output data was stored and used repeatedly by GA for off line parameter estimation. Figure 5 shows the input and output data, which used in simulation.

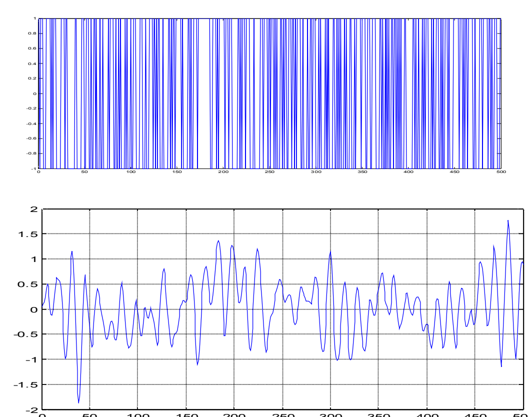

Figure (5) shows input and output signal

7. GA modeling results

The system is corrupted by white noise with standard deviation (0.03) and the GA estimate produced the following parameters after 100 generations, which can be seen in table 2.

Table 2. System parameters after 100 generations

Parameter	Real parameters value	GA Estimated parameters value
a1	0.04046	0.04050
a2	0.00918	0.0091
a3	-0.03323	-0.0332
b1	-2.675	-2.6750
b2	2.557	2.557
b3	-0.8679	-0.8679

From the table2 the estimated parameters are very close to the actual Parameters and the error between real plant and estimated model are decreased and have the value:

$$SSE = 4.4462 \times 10^{-6}$$

Then GA model becomes:

$$H(z) = \frac{y(z)}{u(z)} = \frac{0.04046z^2 + 0.0091z - 0.0332}{z^3 - 2.675z^2 + 2.557z - 0.8679} \qquad (6)$$

The step response of the estimated model compared with real plant illustrated in Figure 6, this figure shows the fit between plant model and GA model and confirms the efficiency of GA in finding a good model for the ball and hoop system.

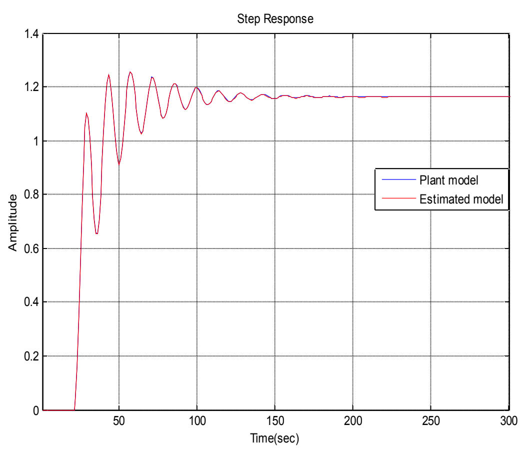

Figure6. Step response of estimated model versus plant model 100 generations.

Figure 7 shows the overlapping between real plant and estimated model. It can be seen that, the two curves are overlapping, this denoted the good estimation which achieved by using GA.

By analyzing the Figure 7, it can be concluded that the GAs parameters were well selected, since in the final generations, a local search was performed, that lead to obtain estimation with a higher accuracy.

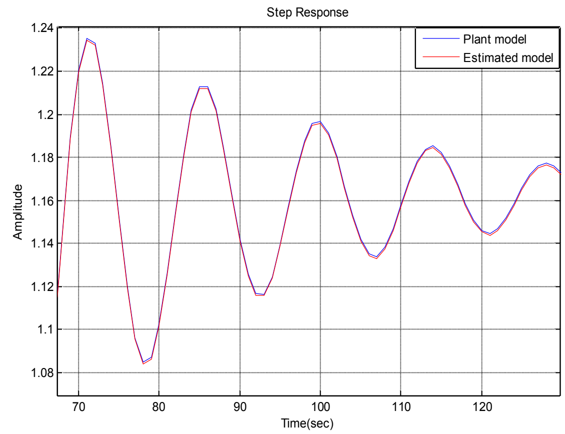

Figure 7. overlapping between real and estimated model

8. Conclusion

In this paper it has been demonstrated that the genetic algorithm can be used for identifying physical parameters of a ball and hoop system.

The process has shown to be powerful, as in the application the basic algorithm stays the same and the GA has been able to converge toward the actual values of the parameters, although there are no known necessary and sufficient conditions for its convergence. In most cases unbiased estimates are obtained. Like the identification of the zeros, convergence is slow, primarily because the objective function is not as sensitive to changes in the zeros as it is to changes in the poles.

The Objective Function is the main ingredient for a genetic algorithm. In this work, this function has been formulated using squared of summation error equation (SSE) which itself uses the present input and output data along with the current estimation of the parameters. In comparison to some widely known identification techniques, least square, which performs as well or even better in terms of number of samples required for converging, and noise signal effected on the least square converging.

The only disadvantage of GA is fairly computer intensive and the convergence time is long for the comparison between LS and GA.

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