International Journal of Engineering and Applied Sciences (IJEAS)
Vol.2, Issue 2(2010)33-43

GA-BASED SERVO SYSTEM PARAMETER ESTIMATION DURING STARTUP

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Accepted Date: 15 October 2009

Abstract

This paper proposed the application of Genetic Optimization Algorithm in estimation of the parameters of servo electrical drives. In comparison with this proposed method, least squared error (LSE) estimation method is considered as a convenient method for parameter estimation. Despite of LSE estimation, GA method is not restricted to the linear systems respect to the. GA is imported as an optimization method in comparison with conventional optimization methods because of its power in searching entire solution space with more probability of finding the global optimum. As a condition for convergence, transient excitation is considered instead of persistent excitation. Finally, comparison between LSE and GA based parameter estimation is presented to indicate robustness and resolution of GA identification method. It will be shown that the GA method of estimation have better results in the start up of the system where there is a lack of persistent excitation.

Keywords: Parameter Estimation, startup, Genetic optimization, Least Square Error Estimation, System Identification, Servo drive.

1. Introduction

Servo drives are widely used as positioning systems in low power industrial applications. In practice, where real data are used, the driver parameters and the system parameters are unknown or varying with load conditions. In this paper, the dynamic treatment of Servo Motor with its driver is considered as the system that must be identified with proposed parameter estimation method [1].
The system identification can be carried out as non-parametric or parametric models. Non-parametric models correspond to such models which described by a function, curve or table. However, in many cases, it is relevant to deal with parametric models. Parametric vectors prescribe such models, which will be denoted by q . We obtain the structure of dynamic model of servo motor When q is varied over some set of feasible values [1].
In general, the experimental condition is a description of how, the identification experiment is carried out. This includes the selection and generation of the sampling interval, the input signal, pre filtering of data prior to estimation of the parameters, etc.. The experimental condition is determined when the characteristic property of system cannot be changed by the user during the data collection.
Recursive LSE and Genetic Algorithm Estimation methods are considered as parametric methods. The performance of LSE method and the genetic algorithm optimization in identifying the dynamic state of servo are compared together. As we see the proposed GA, method shows better estimation of the system parameters during startup while the LSE

cannot converge during such a short period. For better explanation of GA algorithm applied to drive systems the reader is referred to references [6]-[8].
In this paper, we will introduce the application of genetic algorithm optimization in parametric model identification. Minimizing the error function is the key element in obtaining the Unknown parameters. A fitness function according to the sum-squared error must be formulated In order to treat the parameter estimation problem by the GA. The proposed algorithm begins with a collection of parameter estimates (chromosomes), which each one is evaluated for its fitness in solving the given optimization task. In each generation, the chromosomes with higher fitness values are allowed to mate and bear offspring. The children that are new parameter estimates form the basis for the next generation. The use of crossover and mutation cause this algorithm tends to find the global optimum solution without being trapped in local minimum. GA has been successfully applied to a variety of optimization problems, such as image processing, and fuzzy logic controller design [1-2-3]. As it is explained, The transient excitation instead or the persistent excitation in the startup period of the servo system, leads to better parameter estimation with GA based method of estimation.

2. Description of the Method

Assume that **G** is an LTI system with undefined specific model .So we can only guess the type and number of poles of it. $H(s)$ is the estimated transfer function of system and can be expressed as a ratio of polynomials in Laplace domain as follow:

$$H(s) = \frac{\prod_{k=1}^{M}(s - z_k)}{\prod_{k=1}^{N}(s - p_k)} \qquad N \geq M \tag{1}$$

We assume that the system includes N1 real poles and $2 \times$N2 complex poles. The partial fraction expansion of H(s) can be obtained as follow:

$$H(s) = \sum_{k=0}^{N1} H_{1k}(s) + \sum_{k=0}^{N2} H_{2k}(s) \tag{2}$$

Where

$$H_{1k}(s) = \frac{a_{1k}}{s + b_{1k}s} \tag{3}$$

And

$$H_{2k}(s) = \frac{a_{2k}s + a'_{2k}}{s^2 + b_{2k}s + b'_{2k}} \tag{4}$$

Where $a_{1k}, a_{2k}, b_{1k}, \ldots$ are unknown parameters.
The system is excited with a step function as an input to the model.

$$Y(s) = X(s)H(s) \quad \& \quad H(S) = \int_0^{\infty} e^{-st} h(t)dt \tag{5}$$

As a result, the step response of the system is obtained as equation (6)

$$y(t)=\int_0^t h(v)dv \;\;\&\;\; h(t)=\{H(s)\}^{-1} \tag{6}$$

y(t) can be easily calculated in general form. After calculating y(t) corresponding to unknown parameters, the following model is applicable.

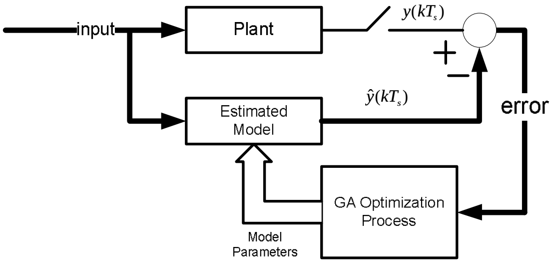

Fig.1. estimation process

In each sample time, T_s, $y(kT_s)$ is real number and $\hat{y}(kT_s)$ is a function of unknown parameters in that sample time. The estimated model can be obtained with any information about the location of poles or guessing the dynamic state of model so if the specific model for the system is available the problem will be too easy.
The aim is minimizing the square of error function and obtaining unknown parameters. Consider $\sum e^2=\sum_{k=0}^{N}(y(kT_s)-\hat{y}(kT_s))^2$ as a fitness function and using Genetic Algorithm Optimization methods for minimizing fitness function. In many situations, we can specify some restrictions for the model parameters, which make the problem more complicated.
in this method according to transient excitation, the settling time is definite and equals to $t_s=NT_s$, where N is the number of samples and will be obtained if the sampling frequency is definite $\left(f_s=T_s^{-1}\right)$.

3. Problem Statement

We want to simulate any servo with estimating the dynamic state of Motor. The state equations of the Motor system are written as follow [4]

$$\frac{di_a(t)}{dt}=-\frac{R_a}{L_a}i_a(t)-\frac{K_b}{L_a}w_m(t)+\frac{1}{L_a}e_a(t) \tag{7}$$

$$\frac{dw_m(t)}{dt}=\frac{K_T}{J_m}i_a(t)-\frac{B_m}{J_m}w_m(t)-\frac{1}{J_m}T_L(t) \tag{8}$$

Where $i_a(t)$ is armature current, and $w_m(t)$ is rotor angular velocity $R_a, L_a, K_b, K_T, B_m, J_m$ are Motor parameters that described in table 1.
According to [4] dynamic treatment of Motor can be modeled as follow:

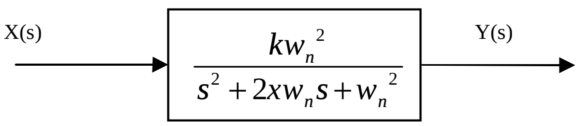

Fig. 2. Second order dynamic model

x is referred as the damping ratio and the parameter w_n as the un-damped natural frequency and k, is the gain of system. We want to identify these three parameters with minimizing the sum of squared errors as in figure 2.

Now consider a tested Motor with the parameters as in table 1.

Table 1. Tested Motor Parameters

Item	**Value**
Resistance R_a	0.8Ω
Inductance L	$5\times10^{-3}H$
Back-emf constant K_b	$8\times10^{-3} V/rpm$
Torque constant K_T	$8\times10^{-3} N.m/Amp$
Rotor inertia J	$1.5\times10^{-5} N.M.S$
Friction coefficient f	$2.5\times10^{-5} N.M/rpm$

According to equations (2)-(4) and figure (2), we have only a second order section.

$$H(s) = H_{20}(s) = \frac{a_{2k}s + a'_{2k}}{s^2 + b_{2k}s + b'_{2k}} = \frac{k{w_n}^2}{s^2 + 2hw_n s + {w_n}^2} \tag{9}$$

H(s) is as Estimated Model then we have:

$$h(t) = \left\{\frac{k{w_n}^2}{s^2 + 2hw_n s + {w_n}^2}\right\}^{-1} = \frac{kw_n}{\sqrt{1-h^2}} e^{-hw_n t}\sin(w_n\sqrt{1-h^2}\ t) \tag{10}$$

$$\hat{y}(t) = \hat{h}(t) * u(t) = k(1 - \frac{1}{\sqrt{1-h^2}} e^{-hw_n t}\sin(w_n\sqrt{1-h^2}\ t + \cos^{-1}h) \tag{11}$$

As a result fitness function is:

$$J = \sum e^2 = \sum_{k=0}^{N}(y(kT_s) - \hat{y}(kT_s))^2 \tag{12}$$

Consider the response of tested Servo Motor to step function:

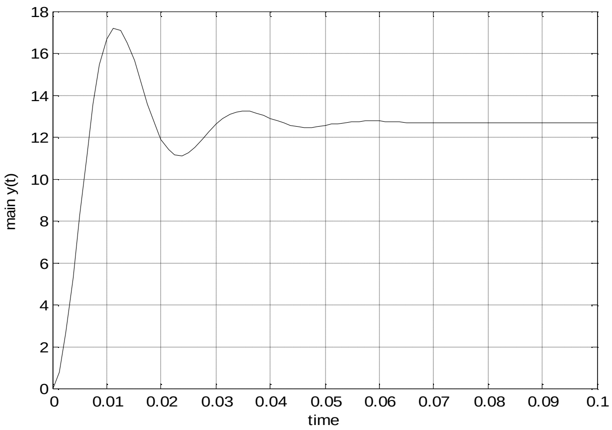

Fig. 3. Step response of tested Motor

Now Genetic Algorithm methods are used for finding unknown parameters. At the end of this paper, Least Squared Estimation (LSE) is used in comparison with the proposed method. The gradient base LSE is used according to transient excitation. For simplifying the comparison, we consider only two unknown parameters, h and k and assume w_n is determined. (Assume w_n =283.5)

4. Parameter Estimation via Genetic Algorithm

The genetic algorithm is a stochastic optimization algorithm that was originally motivated by the mechanisms of natural selection and evolution of genetics. In the following, a parameter estimation algorithm is developed based on GA to evaluate the unknown parameters, by carrying out minimization of the sum squared errors in (12).GA Operators are listed in the following paragraphs[6]-[8].
Genetic algorithm is effective when used with its best operations and values of parameters. The following operators are modified due to experimental results.

1- The fitness function (***J***) is considered as (12) that must be optimized as the objective function.
2- The population size determines the size of the population at each generation. Choosing the population size as 50 will be satisfied the results.
The population can be represented by a 50 by 2 matrix while this optimization includes two variables. In each iteration, a series of computational on the current population is performed by the genetic algorithm, to produce a new population.
The first step in algorithm is creating a random initial population in interval of [0, 2.5] as initial range.

3- At each step, the genetic algorithm the current population is used to create the children that make up the next generation. Individuals with better fitness value are usually selected by algorithm. Selection mechanism, have uniform distribution due to its robustness.

4- Elite children are the individuals with the best fitness values in the current generation that are guaranteed to survive to the next generation. 5 or 10% of population size is considered as elite count. Algorithm is repeated until the number of generations equal to 300, which is the termination criterion.

5- Heuristic crossover and Gaussian mutation step-size are used to produce offspring for the next generation. Gaussian mutation mean operator is set to zero and the standard deviation $d = 5.5$ in this optimization. Heuristic crossover returns a child with a small distance away from the parents with the better fitness value.
The parameter Ratio can specify how far the child is from the better parent. The following equation illustrates the relation between parameter Ratio and child as next generation.
Child= parent #2 + R (parent #1- parent #2)
Where parent #1 has the better fitness value than the parent #2 and R is the parameter Ratio. R=1.2 is considered for second order dynamic model.

6- Hybrid function increases the robustness of genetic algorithm, which is run after the genetic algorithm termination in order to improve the value of fitness function. The Hybrid function uses the final point from the genetic algorithm as its initial point to converge the optimization to the nearest best value that is the global optimum point.
fminsearch is used as the function that is an un-constrained minimization function in the optimization. *fminsearch* uses the simplex search method of [5]. This direct search method does not use gradients. The results of GA Estimation are collected in table (2).

Table 2. Genetic Estimation Results

State No.	Sampling Time (sec.)	Number of Data points	Estimated Parameter k	Estimated Parameter	Gain error %
1	0.0025	20	12.67373	0.3291	0.0046%
2	0.00125	40	12.66903	0.3142	0.0325%
3	0.0005	100	12.66502	0.3124	0.0642%

The equation (9) can be written in time domain as follow:

$$\frac{d^2 y(t)}{dt^2} + 2hw_n \frac{dy(t)}{dt} + w_n{}^2 y(t) = kw_n{}^2 x(t) \qquad (13)$$

Digitization is the first step in LSE modeling, which is carried out by the following differentiation approximation.

$$\frac{dy(t)}{dt} = \frac{y(t) - y(t - T_s)}{T_s} \qquad \text{for } T_s << 1 \qquad (14)$$

In general form, any other approximations can be used. The digitized model can be written as:

$$\begin{aligned} & y(t) - 2y(t - T_s) + y(t - 2T_s) + w_n{}^2 T_s^2 y(t - 2T_s) + \\ & 2hw_n T_s \left[y(t - T_s) - y(t - 2T_s) \right] = kw_n{}^2 T_s^2 x(t - 2T_s) \end{aligned} \qquad (15)$$

$w_n T_s = a$ so the model structure can be written as follow:

$$\Psi(t) = j^{T}(t) q \tag{16}$$

$$\Psi(t) = y(t) - 2y(t-T) + y(t-2T) + a^{2} y(t-2T) \tag{17}$$

$\Psi(t)$ is measurable quantity. (18)

$$j^{T}(t) = \left[2a\,(y(t-2T) - y(t-T)) \qquad a^{2} x(t-2T) \right] \tag{19}$$

$$q(t) = \begin{bmatrix} h \\ k \end{bmatrix} \tag{20}$$

$q(t)$ is a two vector of unknown parameters.

$$\hat{q} = \left[\sum_{t=1}^{N} j(t) j^{T}(t) \right]^{-1} \left[\sum_{t=1}^{N} j(t) \Psi(t) \right] \tag{21}$$

After using gradient base LSE [1], h and **k** will be obtained. The results of LSE Estimation are collected in table (3).

Table 3. First Estimation Results

State No.	Sampling Time (sec.)	Number of Data points	Estimated Parameter k	Estimated Parameter	Gain error %%
1	0.0001	500	12.6730	0.3244	0.0012%
2	0.00005	1000	12.6731	0.3174	4.0489e-4%
3	0.00001	5000	12.6731	0.3117	4.0489e-4%

5. Practical experimental setup

The experimental setup consists of a servo with 1KW rating that is connected to the load via a precision 1:30 gearbox as in figure 5. An incremental Encoder is coupled to the Servo output to measure the speed of the servo system.
The speed output is fed to the servo driver as an internal feedback to make the system as linear as possible. The data accusation system is a rack-mount controller system that is FPGA base and is supervised from the PC via USB2 serial port connection as in figure 6. Computer is used in the system to receive commands and set points from the user and apply it to the servo setup. The Computer has the authority to stop the process, the data is gathered in the computer, the GA process algorithm is run, and the results are saved as the system setup. The experimental results are shown in the next section.

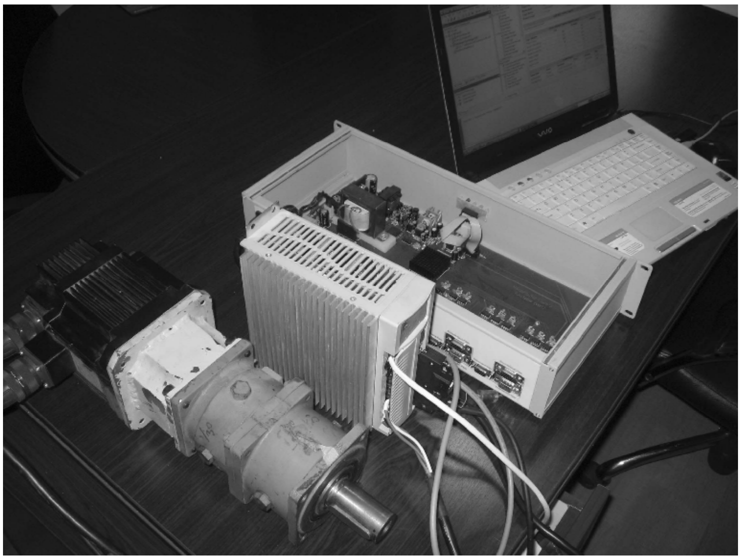

Fig. 5. Experimental setup

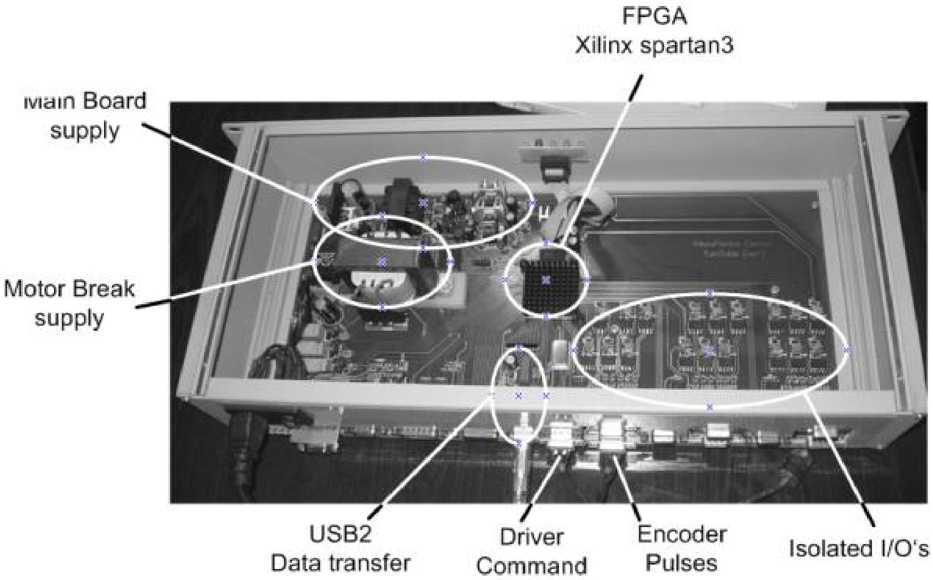

Fig. 6. system FPGA Based controller

6. GA-estimation in comparison with LSE-estimation

The difference between GA Estimation and LSE Estimation in servo start up will be remarkable when the number of data points decrease. The results of practical experimentation illustrate that, high resolution in estimation using LSE method will be obtained since increasing data point numbers and increasing the frequency of sampling. with same data point numbers , the robustness of GA Estimation can be compared with LSE Estimation , figures (7,8,9,10) indicate the resolution of estimation using GA & LSE methods with N=20 , N=40. Table (4) and Table (5) show the resolution of each method.

Remark 1: Gain error percentage is defined as

Gain error [%]=

$$\left|\frac{estimated\ gain - main\ gain}{main\ gain}\right| [\%]$$

Remark 2: shaping factor can be defined as:

Resolution Factor = $(1-\frac{h_{estimated}}{h_{main}})\times 100\%$

Note: of course h_{main} and main Gain are not available but we can assume (only for comparison) that Motor parameters in table 1 are available.

Table 4. comparison between GA & LSE methods for N=20, 40

Estimation method	Sampling Time (sec.) T_s	Number of Data points N	Estimated Parameter k
1-GA	0.0025	20	12.67373
2-LSE			12.6835
1-GA	0.00125	40	12.66903
2-LSE			12.6732

Table 5. comparison the resolution of two methods for N=20, 40

Estimation method	Number of Data points N	Estimated Parameter *h*	Resolution Percentage %
1-GA	20	0.3291	93.94 %
2-LSE		0.6540	10.76 %
1-GA	40	0.3142	98.74 %
2-LSE		0.4825	44.50 %

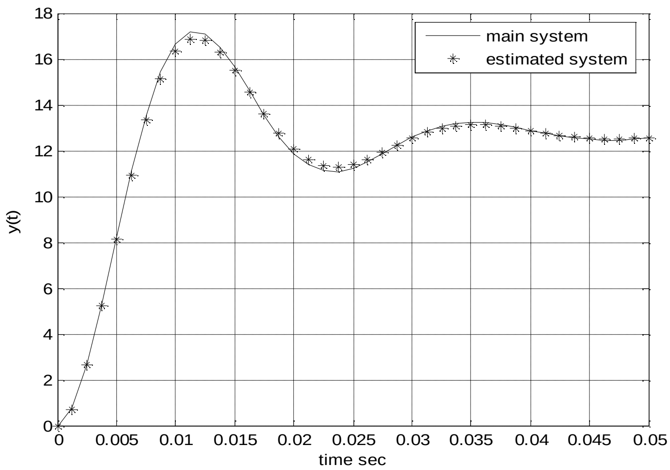

Fig. 7. GA Estimation for N=20(resolution =93.94%)

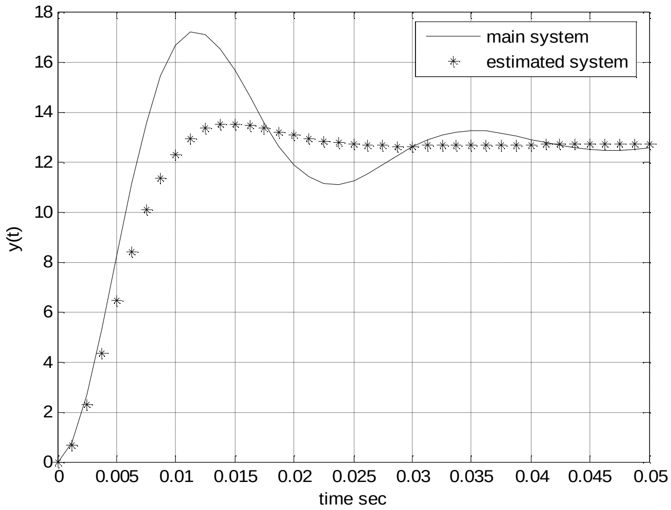

Fig. 8. LSE Estimation for N=20(resolution =10.76%)

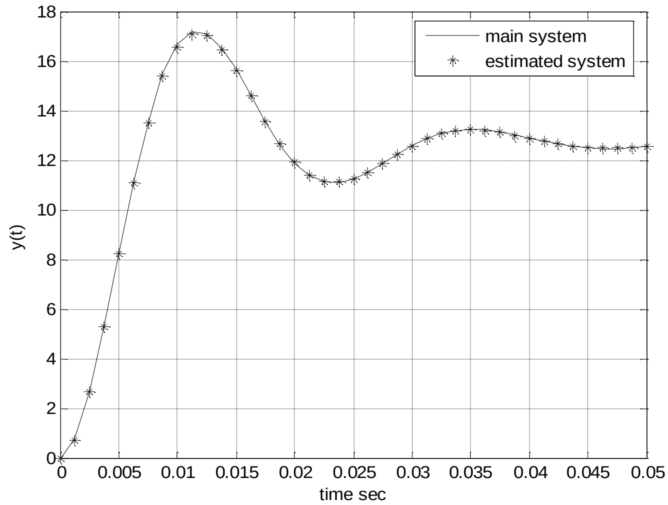

Fig. 9. GA Estimation for N=40(resolution =98.74%)

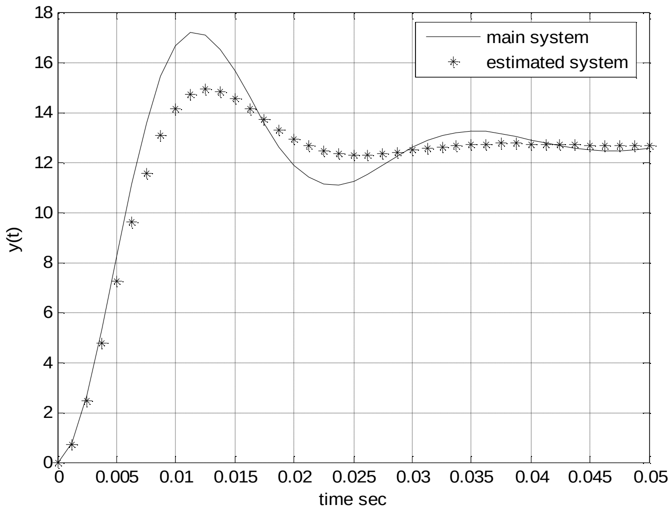

Fig. 10. LSE Estimation for N=40(resolution =44.50%)

7. Conclusion

The dynamic model of closed loop Servo was described with two methods: LSE estimation and GA estimation. This proposed method is applicable in off line parameter estimation, according to robustness of GA optimization in finding global optimum in nonlinear models with respect to estimated parameters. The GA method is able to estimate parameters in high resolution.

Since the number of data points in GA estimation algorithm is fewer than the number of data points in LSE estimation, this method provides accurate estimates of parameters. Accurate estimation of the parameters is satisfied with this method, especially the estimation of parameter h that is important in identifying the dynamic state of model.

Despite of LSE estimation, GA estimation can be used for systems that are not linear due to parameters.

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