A SURVEY OF IDENTIFICATION EXPERIMENTAL SYSTEM PARAMETERS USING GENETIC ALGORITHM

Trong-Bang Tran, Tran-Khanh-Vy Dang, Minh-Nhut Phan, Binh-Duong Tran, Van-Duc Trinh, Huynh-Quoc-Bao Nguyen, Thi-Thien-Trang Vo, Thi-Thanh-Hoang Le*

Ho Chi Minh city University of Technology and Education (HCMUTE)
Vo Van Ngan street, No. 01, Ho Chi Minh City, Vietnam
***** Corresponding author. E-mail: hoangltt@hcmute.edu.vn

Abstract: System parameter identification is the process of finding system parameters to convert physical control signals (usually torque) from theoretical controllers into signals that the hardware can generate for communication connected to model's executive structure. Simple SIMO systems, like balanced vehicles, often employ PID controllers due to their straightforward design and effectiveness. The algorithm's simplicity is extensively elucidated in document [1]. Linear controllers and their parameters are typically determined through experimentation and expert knowledge. However, for advanced controllers such as LQR, H Infinity, and SMC, a trial-and-error approach is not viable due to their complexity and the need for precise tuning.
Keywords: SIMO system, Genetic Algorithm, LQR algorithm.

1. Introduction

SIMO (Single Input Multiple Output) systems represent highly nonlinear control objects, often characterized using Euler-Lagrange method, incorporating summation of kinetic and potential energies. Input-impacting state variables encompass physical interactions or environmental disturbances. Achieving successful control of SIMO systems serves as benchmark to assess controller quality. Advanced control methodologies commonly taught in academia, such as in [2], the authors have effectively implemented the Linear Quadratic Regulator (LQR) algorithm to regulate balance and has integrated the swing-up algorithm to broaden the operational range.

Another nonlinear algorithm we have learned is Sliding Mode Control (SMC), which demonstrates impressive trajectory tracking capabilities as demonstrated in [4]. Because it relies on Lyapunov stability theory, SMC controller also requires standard identification of system parameters. Recently, a study on Backstepping algorithm has been published in [3], aiming to maximize the viability region of inverted pendulum. Therefore, modulation of standard control signals is crucial. For some complex SIMO systems, more advanced algorithms will be applied, such as, H-infinity control defined in [5], and Model Predictive Control (MPC) evaluated for quality in [6]. Both controllers not only require standardization of model parameters of actuator but also demand accurate state equations of SIMO system. In simulations, most controllers effectively control SIMO systems by utilizing optimization algorithms to tune parameters. In [7], Katoch provides a detailed analysis of genetic algorithm (GA). This is an evolutionary algorithm commonly used in education. In [8], author Fu introduces and evaluates Particle Swarm Optimization (PSO) algorithm in detail. This method utilizes swarm intelligence to search for suitable parameter sets. However, these control signals predominantly manifest as torque or thrust, necessitating conversion into voltage values for motor input. This transition exposes inherent characteristics and properties of new controllers within simulation environment. System identification, a field studied by experts for decades, continues to encounter unresolved challenges.

In [9], a standardized identification method is proposed, leveraging the motor's state equation. Control quality validation has been substantiated through experiments governing SIMO systems. Nonetheless, a notable issue arises with current transformer within this equation, as it is prone to significant noise and measurement errors due to voltage signal's Pulse Width Modulation (PWM) format and considerable delay compared to mechanical speed. In this article, we present a novel approach derived from the proposed state equation, employing a new search and data processing technique that circumvents the need for measuring current signals while still yielding the most optimal parameter set through a migration algorithm, thus enhancing result optimization.

2. Mathematical Model

From [9], the authors used a state equation to approximately describe nonlinear state of a DC motor in Fig. 1 below. Provided block diagram illustrates correlation between speed of a DC motor and input voltage. Subsequently, it becomes imperative to gather data on actual voltage and corresponding speed response of physical motor, serving as foundation for further investigation and analysis.

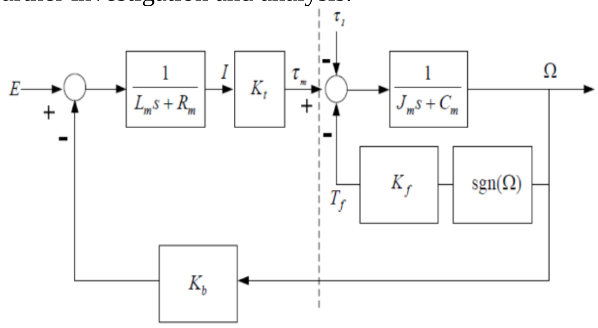

Fig. 1. Mathematical model of motor DC

where:

R_m: motor resistance (ohm) (have to find)
L_m: reactance coefficient (H) (have to find)
K_b: counterelectric constant (V/(rad/sec)) (have to find)
K_t: Is chosen to be equal to K_b
J_m: moment of inertia of the rotor (kgm^2) (have to find)
C_m: viscous friction coefficient (Nm/(rad/sec)) (have to find)
T_f: friction moment (Nm) (have to find)
τ_1: resisting moment (Nm)
ω: motor speed (rad/s)
τ_m: internal torque (Nm)
θ_m: internal torque (rad)

3. Hardware

In order to comprehensively capture diverse operational states of DC motor, our approach involves generation of a range of voltage patterns. We have opted for STM32F407VG (in Fig. 2) microcontroller to serve dual roles in both control and data acquisition. This selection is primarily motivated by its cost-effectiveness, being the most economical option among microcontrollers supported for direct embedding from .mdl file in Matlab/Simulink. Leveraging this microcontroller enables the development of control algorithms in a straightforward manner, minimizing costs associated with programming and hardware.

Fig. 2. MCU STM32F407VG

Fig. 3. BTS7960 H bridge

Fig. 4. Power supply 12V

Fig. 5. Motor DC nisca b3015600b

In terms of the motor, we choose Nisca B3015600B DC motor (in **Fig. 5**) due to its relatively large torque and built-in encoder, making it suitable for controlling SIMO models. To ensure that this motor operates at maximum efficiency, we have opted to use BTS7960 H-bridge (in Fig. 3) circuit, which boasts a transmission efficiency of up to 98% and can withstand voltages of up to 35V according to manufacturer's specifications. These components are carefully selected to optimize cost-effectiveness and performance.

4. Software

4.1. Data Collection Software

With support of Simulink control code, main structure is shown in Fig. 6 below.

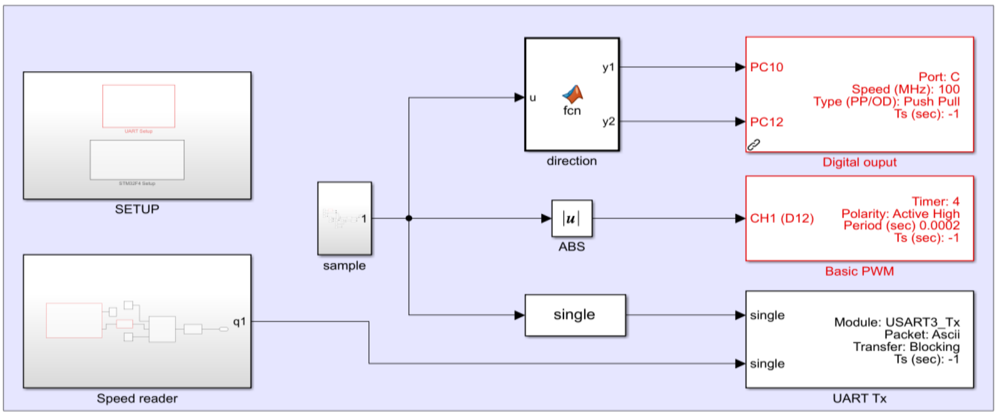

Fig. 6. Voltage modulation program

Detail:

"SETUP" block is responsible for configuring hardware parameters to align with chosen microcontroller (MCU) and communication module. Following this, "sample" block is employed to generate a range of voltage variation states. Subsequently, "Basic PWM" block facilitates generation of PWM signals, while "Digital Output" block governs adjustment of motor's rotation direction. Upon completion of aforementioned processes, "Speed reader" block decodes signal and computes speed based on encoder signal. Subsequently, acquired data is transmitted using UART protocol, facilitated by "UART Tx" block.

Crucial point here is "sampling" block. It generates voltage waveforms with various transformation states. This helps to achieve widest possible coverage in collected dataset.

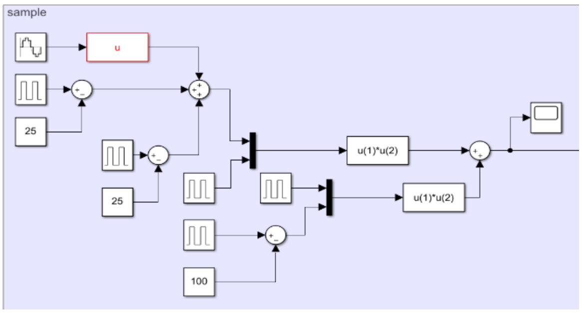

Fig. 7. "Sample" block

By compensating for both square and sine waves signals appropriately, we have successfully modulated sine waves in both positive and negative voltage regions. Additionally, square wave signals are included to detect motor's dynamic state during voltage reversal.

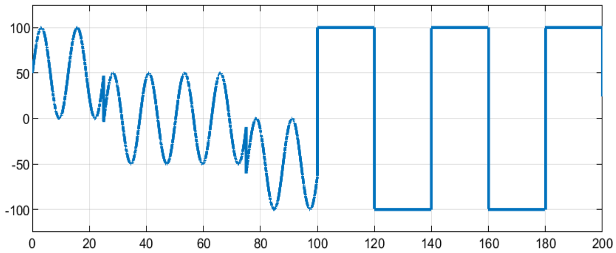

Fig. 8. Duty cycle graph

With a UART data reading time of 100ms, we have chosen a data collection time of 200 seconds, which is equivalent to 2000 data points.

4.2. GA Loop Software

We utilize GA to search for system parameters. Motor operation process is simulated in Simulink, and objective is to find a state equation for motor that closely matches dataset collected from experiments.

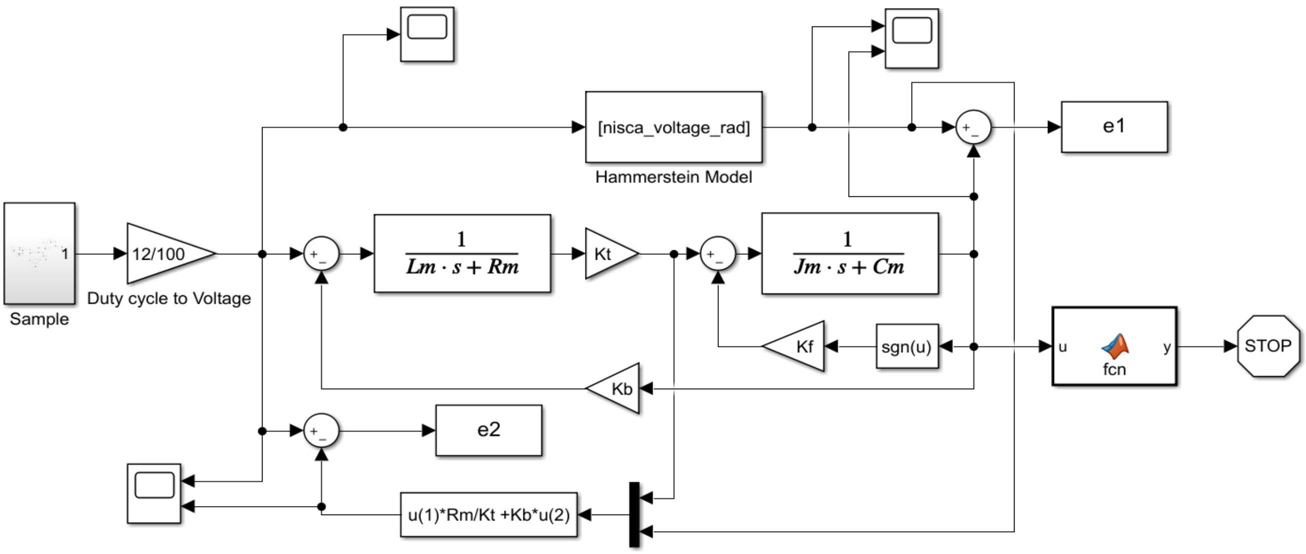

Fig. 9. GA program

From block diagram in **Fig. *1***, we constructed them in rectangular box outlined in red in **Fig. *9***. "Voltage" block in **Fig. *9*** represents formula for converting torque into voltage applied to motor. From [9], page 25, equation 4.26, we derived following formula:

$$e = \frac{R_m}{K_t}\tau_1 + K_b\dot{q} \qquad (1)$$

where: *e: voltage supplied to the motor;* $\dot{q}$ *: angular speed of the motor*

With data obtained, we identified transfer function with voltage input and angular velocity output. The "Hammerstein Model" block represents the transfer function identified from dataset using System Identification toolbox of Matlab. It has very high accuracy, up to 98% of dataset, and also serves purpose of filtering data noise and reducing simulation cycle time, significantly enhancing efficiency of GA.

Chosen objective function has the following form:

$$J = \sum_{i=1}^{n} [e_1 e_1' + e_2 e_2'] \tag{2}$$

where:

e_1: *objective function selected is error between angular velocity of transfer function and angular velocity of mathematical model of motor.*

e_2: *objective function selected is error between input voltage and voltage calculated from formula (1).*

"Stop" block is activated when "fcn" block precedes that it receives a value u beyond Matlab's computational range to prevent Matlab memory overflow errors.

5. Data Collection, Processing, and Application of GA

5.1. Data Collection, Processing

Because UART compiling software has limited memory, we collected data over 150 seconds, resulting in a dataset of 1500 data points.

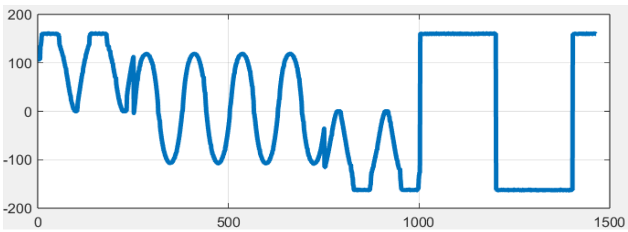

Fig. 10. Data set of angle velocity

This dataset has undergone simple noise processing, hence the graphs may exhibit slight distortions at some points. During GA loop execution, accessing individual data points would consume significant resources, significantly increasing time required. Therefore, we use System Identification toolbox to find a standard transfer function describing this dataset.

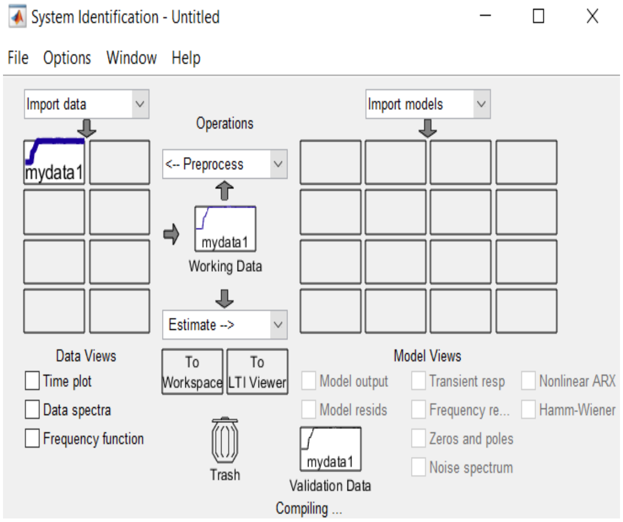

Fig. 11. System Identification app display

Fig. 12. shows data collected by program in Fig. 6.

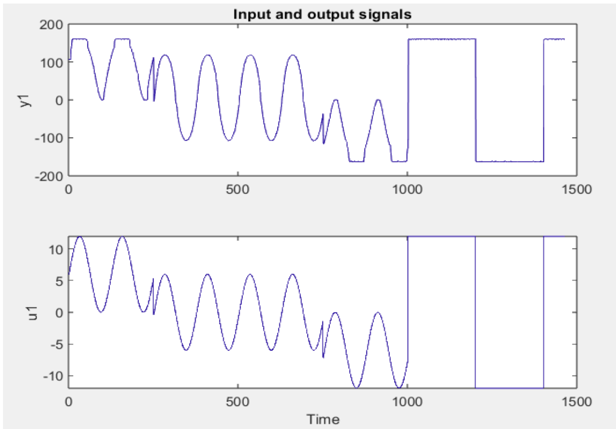

Fig. 12. Data Identified

The chosen estimation method in this context is nonlinear modelling. Within the realm of nonlinearity, we utilize Saturation type for input and Piecewise Linear type for output. Through this configuration, we have achieved the optimal quality transfer function, enhancing accuracy and fidelity of our modelling approach.

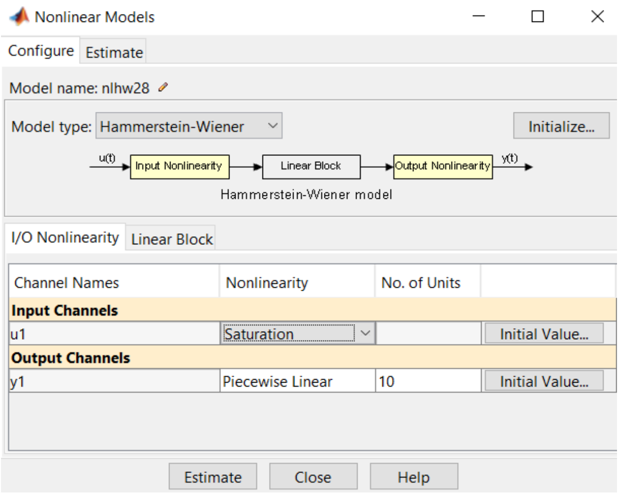

Fig. 13. Nonlinear Models display setting

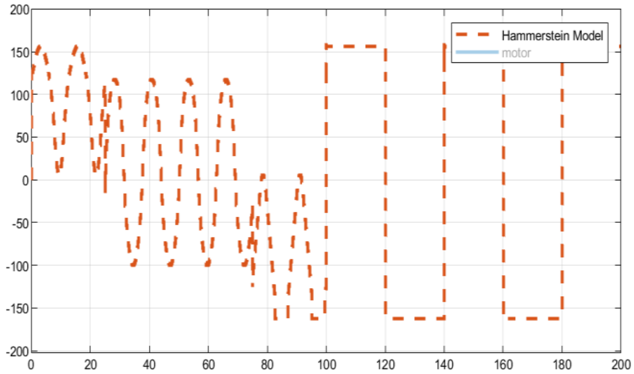

Fig. 14. Identified transfer function has most standard quality

5.2. Genetic Algorithm

We choose configuration parameters for GA as:

- Maximum number of generations: 200;
- Number of individuals: 70;
- Hybridization coefficient: 0.6;
- Mutation coefficient: 0.4;
- Encoding type: binary encoding;

After 200 generations, we get the following results: $R_m = 2.826$; $L_m = 0.0452$; $K_b = 0.0061$; $J_m = 0.0023$; $C_m = 0.0023$; $K_f = 0.0000519$; $K_t = 0.0926$

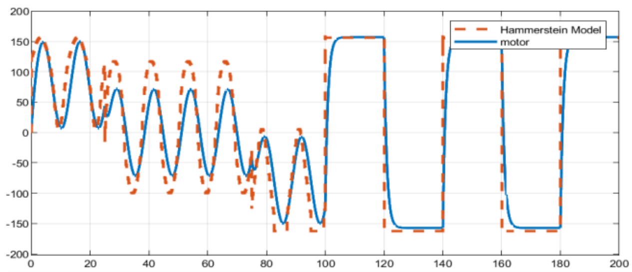

Fig. 15. Error between ouput transfer function and mathematic of motor

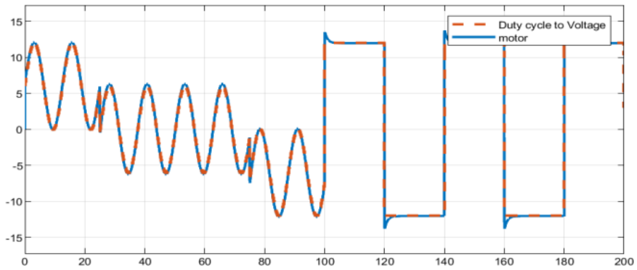

Fig. 16. Error between voltage supplied to the transfer function and voltage calculated from equation (1)

In Fig. 15, velocity of mathematical model in Fig. 1, while slightly delayed, still maintains relatively standard values. In Fig. 16, using torque from mathematical model and velocity from identified transfer function, we obtain voltage values that are almost accurate via formula (1).

6. Verified through Control Algorithm

In [10], we announced the successful control of Pendubot using LQR algorithm with system identification method in this article.

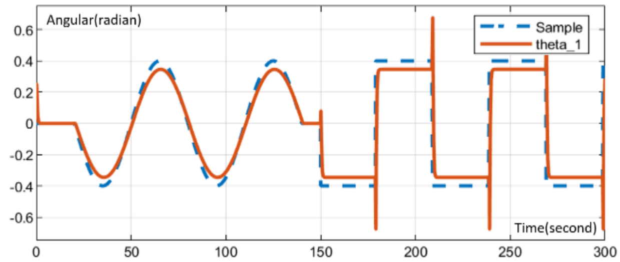

Fig. 17. Trajectory tracking control in simulation

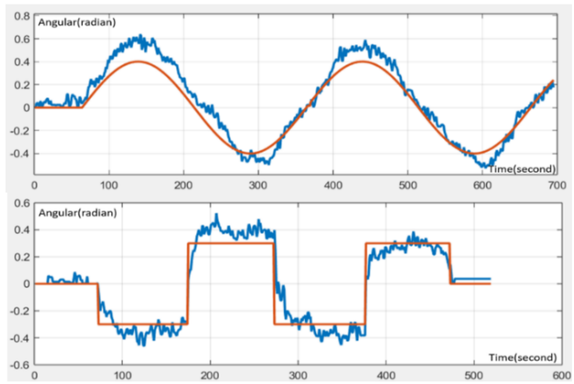

Fig. 18. Trajectory tracking control in experimental model

In simulation, variables exhibit a finer granularity compared to experimental data and may not precisely adhere to predefined trajectory. This discrepancy does not stem from technological limitations but rather from inherent constraints of sensors, which do not possess same level of resolution as simulated data.

7. Conclusions

In this newly proposed identification method, not only does it simplify recognition process, but it also significantly improves accuracy of simulation system parameters compared to real systems. It reduces the discrepancy between simulation and experiment, making application of simulated parameters to real systems more effective. This opens the door for new entrants to control algorithms, such as students, enabling them to easily access and experiment with system description parameters at lower equipment costs. Furthermore, this method also opens up new avenues of thinking when dealing with incomplete input data processing methods for system parameter collection indirectly.

8. Acknowledgement

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