Review of Method for System Identification on Motors

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Abstract—**The industry is closely related to motors. Motor is used as the prime mover to run the production machines. Control of the motor is needed so that it can work according to its designation. Motor parameters must be known to control it. The required parameters include electrical and mechanical parameters. These parameters are often not easy to obtain then one way to find out is by identifying the system. This paper aimed to convey the various methods that have been used in motor identification systems. Brushed DC motor, brushless DC motor, servo motor, stepper motor, induction motor, and switch reluctance motor were motors analyzed. These methods included the least square, recursive least square in the form of autoregressive with exogenous input, autoregressive moving average with exogenous. Another system identification method utilizes artificial intelligence. This method used fuzzy logic, neural network, genetic algorithm, particle swarm optimization, and various combinations of these methods. The review results showed that the artificial intelligence method was very interesting and promising because it has advantages compared to conventional methods. Modification or combination of two or more artificial intelligence methods would get better and closer results to the actual situation.**

Keywords—system identification, method, motor.

I. INTRODUCTION

Motors is a very important tool in the industrial world. Motors are the main driving force in production machines [1]. In addition, motors are also used in everyday human life. Whether it's for facilities such as electric cars, electric motorcycles, electric bicycles, as well as in household appliances such as fans, cooking utensils, cleaning tools, and others [2]. From this fact, it can be said that humans cannot be separated from the role of motors in their lives.

In its use, of course, this motor requires a control so that it can be used according to its function. To control it, knowledge of the parameters in the motor is needed [3][4]. In the motor there are two important parameters are electrical and mechanical parameters. Electrical parameters include electromagnetic force, resistance, inductance, current, voltage. Mechanical parameters include damping ratio, friction, torque. But there are also many motors whose specifications are incomplete and even non existent. In fact, with clear and complete parameter values, a good and precise control can be obtained.

To overcome this problem, several methods of system identification can be used. By providing a certain input signal to the motor, a response from the motor will be generated [5]. If the response of the output response to the input is known, a transfer function will be obtained which is very useful for the world of control. Determination of the mathematical model that is considered appropriate through the previous system identification stage which includes the input signal that has been designed to enter the system, the input and output of the tested data, the selection of the model to be used, the error value obtained [6].

Linear and non-linear systems can be identified through system identification. Determining the system model, determining the error value, and based on the smallest error value in the modeling, the appropriate mathematical model is obtained, which is the basis for identifying conventional systems. Conventional methods have advantages and disadvantages. For online systems, this method is very suitable for system identification, but on the other hand, this method is not suitable for non-linear systems. Least square method is an example of a conventional method [7]. The use of artificial intelligence such as fuzzy logic, neural networks, genetic algorithms, particle swarm optimization is a more modern method in the field of system identification. This method can cover the weakness of the conventional method when it is used in a non-linear system [8].

This paper presents various ways of system identification that have been carried out by researchers to obtain the required motor control parameters. The motors that have been used for analysis to obtain the mathematical modeling are brushed dc motors (BDC) [9], brushless direct current (BLDC) motors , servo motors [10], stepper motors [11], [12], induction motor (IM) [13], , and switch reluctance motor (SRM) [14].]. The methods and algorithms as well as tools used in the identification of motor systems are presented in a comprehensive manner. These methods include the least square method [7][15][16] , recursive method [3][17], using autoregressive with exogenous input (ARX) [18], autoregressive moving average with exogenous input (ARMAX) [19],], and so on. In addition to the methods commonly used for system identification, this paper also presents a system identification method that uses artificial intelligence. These methods include fuzzy logic [20], artificial neural network [21], genetic algorithm [22], and particle swarm optimization (PSO) and various variations between methods [23] [24][25][26][27].

II. SYSTEM IDENTIFICATION

A. Concept of System Identification

The basis of system identification is to find a mathematical model of a dynamic system. The processes that occur in system identification are data taking, formatting (selection model), processing (modeling), and identification (validation) of data obtained from real plants. Figure 1 shows the process. If the mathematical model obtained is considered sufficient to represent the real system, the process stops. But if the model obtained is not satisfactory for the researcher, it will be carried out continuously [5] [28].

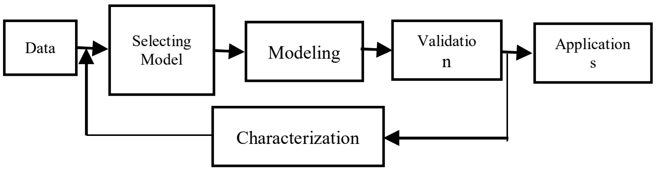

Fig 1. Block Diagram of System Identification

Mathematical models of linear systems in the form of polynomials or state spaces are calculated by parametric and non-parametric methods. Examples of this method are AR, ARX, ARMAX, OE, BJ [29].

The selection of the order/order model is very important so that three standard criteria are known, namely FPE (Akaike's final prediction error criterion), AIC (Akaike's information theoretical criterion), MDL (Minimum description length criterion). In addition, pole and zero plots can be used if you want to get a good mathematical model.

B. Least Square and Recursive Square Estimation

The simplest type of parametric model is the linear regression [30]. The regression model is given in the equation:

$$y = \varphi_1\theta_1 + \cdots + \varphi_n\theta_n \tag{1}$$

$$y = \begin{bmatrix}\varphi_1 & \cdots & \varphi_n\end{bmatrix}\begin{bmatrix}\theta_1 \\ \vdots \\ \theta_2\end{bmatrix} \tag{2}$$

$$y = \varphi\theta \tag{3}$$

Where y is observed variable with a known value, , φ is a regression variable with a known value, dan θ is vector parameter being sought.

If it is assumed that there are m data on y and φ, then equation (2) become:

$$\begin{bmatrix}y_1 \\ \vdots \\ y_m\end{bmatrix} = \begin{bmatrix}\varphi_{11} & \cdots & \varphi_{1n} \\ \vdots & \ddots & \vdots \\ \varphi_{m1} & \cdots & \varphi_{mn}\end{bmatrix}\begin{bmatrix}\theta_1 \\ \vdots \\ \theta_n\end{bmatrix} \tag{4}$$

$$Y = \Phi\theta \tag{5}$$

In the actual calculations found errors that must be taken into account. This is known as equation-error vector or prediction-error vector, E.

$$E = \begin{bmatrix}e_1 \\ \vdots \\ e_m\end{bmatrix} \tag{6}$$

$$E = \begin{bmatrix}y_1 - \varphi_1\theta \\ \vdots \\ y_m - \varphi_m\theta\end{bmatrix} \tag{7}$$

$$E = Y - \Phi\theta \tag{8}$$

$V(\theta)$ defined as the following equation;

$$V(\theta) = e_1{}^2 + e_2{}^2 + \cdots + e_m{}^2 \tag{9}$$

$$V(\theta) = E^T E \tag{10}$$

The minimum value of $V(\theta)$ can be obtained by getting the derivative of V with respect to θ is equal to zero because $V(\theta)$ is a quadratic function of the unknown parameter. So that the equation is obtained:

$$\frac{dV(\theta)}{d\theta} = 2\Phi^T\Phi\theta - 2\Phi^T Y = 0 \tag{11}$$

$$\Phi^T\Phi\theta = \Phi^T y \tag{12}$$

So it will get

$$\theta_{LS} = (\Phi^T\Phi)^{-1}\Phi^T Y \tag{13}$$

System identification can be described in general in the equation (14):

$$A(q)y(k) = \frac{B(q)}{F(q)}u(k - nk) + \frac{C(q)}{D(q)}e(k) \tag{14}$$

Where:

$$A(q) = a_1q^{-1} + a_2q^{-2} + \cdots + a_{na}q^{-na}$$

$$B(q) = b_1q^{-1} + b_2q^{-2} + \cdots + b_{nb}q^{-nb}$$

$$C(q) = c_1q^{-1} + c_2q^{-2} + \cdots + c_{nc}q^{-nc}$$

$$D(q) = d_1q^{-1} + d_2q^{-2} + \cdots + d_{nd}q^{-nd}$$

$$F(q) = f_1q^{-1} + f_2q^{-2} + \cdots + f_{nf}q^{-nf}$$

$$y(k) = output$$

$$u(k) = output$$

$$e(k) = noise$$

Variation of polynomial A, B, C, D, F determine the structure of the obtained model [31] as shown in Table 1.

TABLE I. MODELS STRUCTURE [31]

Structure	***Model***
B	AR (AutoRegresive)
C	MA (Moving Average)
A C	ARMA (AutoRegresive Moving Average)
A B	ARX (AutoRegresive with Exogenous Input)
A B C	ARMAX (AutoRegressive Moving Average with Exogenous Input)
A B D	ARARX
B F	Output-Error (OE)
B F C D	Box-Jenkins (BJ)

The black box method has the advantage of not needing to know in advance the type and material of the system to be modeled [32]. One algorithm that uses the black box method is recursive Least Square (RLS). As This method is a development of the least square method that has been described previously. The advantage of this method is that it can be used to get a mathematical model of a system online. One solution to speed up obtaining a new mathematical model is to utilize the existing data. This method is often called the Recursive Least Square (RLS) method) [33].

The equation of Recursive Least Square is as follows:

$$\theta_n = \theta_{n-1} + K_n\varepsilon_n \quad (15)$$

where

$$\varepsilon_n = y_n - \Phi_n^T\theta_{n-1} \quad (16)$$

θ_n is parameter vector sought

ε_n is the difference that occurs between the measurement output and the estimated output at time n.

Kalman gain is K_n with equation:

$$K_n = P_n\Phi_n \quad (17)$$

Error covariant matrix defined as:

$$P_n = (P_{n-1}^{-1} + \Phi_n\Phi_n^T)^{-1} \quad (18)$$

To get a model that is close to the actual system, it is necessary to determine the appropriate values of θ_{n-1} and P_{n-1} corresponding [34].

C. Arificial Inteligence

A more modern method is one that uses artificial intelligence. These methods include fuzzy logic, artificial neural networks, genetic algorithms, PSO, and various combinations of these methods. Constraints encountered in the previous methods can be overcome by this method. These constraints are like when looking for parameters in a non-linear system [35]. Fuzzy logic goes through three processes, namely fuzzification, inference, and defuzzification. The rule base is the rule used in this method [36]. Two methods that are often used are the Mamdani and Sugeno methods. Several identification systems have used the fuzzy logic method [37]–[39]. Artificial neural network is also a method used in system identification. This method is based on continuous training to get the desired weight. The training process will stop by limiting iterations or by getting the smallest possible error. Artificial neural network was used to find parameters in previous studies [40]–[44]. Another modern system identification is using genetic algorithms. This method is based on the evolution that occurs to the new chromosomes forming a better individual than before. These studies [45]–[48] are studies that use a genetic algorithm approach.

Similar to genetic algorithms, PSO is also an algorithm that imitates processes that occur in living things. In this algorithm, the social behavior of living things to survive in their group is used to get the desired optimization value. Some studies that use the PSO method are this [49]–[52].

III. Motors System Identification Methods

The explanation used in this motor parameter identification system is based on the method used. Starting from the conventional method, namely the least square method, followed by refinement of this method, namely the recursive method, methods with various forms such as ARX, ARMA, ARMAX, to methods that use artificial intelligence such as fuzzy logic, artificial neural networks, neuro fuzzy, genetic algorithms, PSO, and various combinations thereof. The necessary tools and supporting hardware were also presented in the discussion.

A. Least Square and Recursive Least Square Method

The least square method was used in this study to obtain the modeling of the BLDC motor system [53]. BLDCM ZW60BL120-430 has a specification, 250 W, 3000 rpm, 48 V, 7 A, and 2-pole. The required parameters were obtained by finding the transfer function in a discrete form with the transformation-Z.

The research has been done on AC servo motor was to obtain transfer function then observe the Nyquist diagram [15]. The results of this study indicated that the ARX method has results that were close to the plant. In other words, the ARX identification system managed to get the required parameters better than the IV4 method.

Extrapolative and Least Square methods were compared in the study to obtain parameters for the induction motor with specifications 5 hp, 3420-3480 rpm, 12/6 A [54]. The results showed that with the least square method, better modeling is obtained than the extrapolative method.

BLDC motor used in agricultural robots were searched for electrical and mechanical parameters using the recursive least square. The parameters found were resistance R, inductance L, inertia J [55]. By comparing 1st order, 2nd order, and 3rd order of the transfer function obtained, it has been found that the closet to the real parameters was 3rd order system [23]. The recursive least square method was used in this study to obtain parameters for DC motors [56]. The parameters were found in the transfer function of order 3. The values of a_1, a_2, a_3, b_1, b_2, b_3, mathematical model obtained proved to be very good if it was used for controls. Electrical and mechanical parameters of the SRM Motor could be obtained well in this study [14]. The motor used was a 3-phase 12/8 with several parameters included. The parameters found by the method were phase resistance R, aligned inductance l_0, unaligned inductance l_1, inertia J, viscous friction B, coulomb friction C, and drag D.

The ARX method has also been used for a DC motor identification system. To obtain the required identification system model of DC motor, different sampling times were used in 4 criteria, including 1 ms, 45 ms, 50 ms, and 55 ms. The results that have been obtained show that with a sample time of 55 ms using Loss Function, FPE, AIC the best value was 87.79% [18]. The high order (2nd order) of the transfer function found closer to the actual parameters [57].

Induction motors have also been investigated to obtain the parameters by the recursive method. The model used was a transfer function of 6th order and 22nd order. The 300 Watt induction motor used has a speed of 2870 rpm with a torque of 1 Nm at a frequency of 50 Hz with a working voltage of 380 V [58]. Although the modeling 22nd order has a small error, the model with the 6th order was chosen because of the speed factor.

Another interesting method to study was system modeling using the Taylor series method. The step used was to take a sample of the motor speed response which was at a voltage. These were used as coefficients of power term in the Taylor series. The coefficient could be obtained from the electrical and mechanical constants of the motor, back emf, and friction [59].

Extended Kalman Filtering (EKF) was used as a method to obtain parameters for induction motors [12] [60]. The specification of the induction motor was to work at 380 V, 50 Hz, 3.4 A, 1.5 KW, and 3000 RPM. The parameters found were rotor angular speed and rotor flux.

B. Artificial Intelligence

Research on induction motor 1000 to 1200 RPM found a transfer function 2nd order. The two models (loaded and unloaded) were formed in a feed-forward neural (FFN) which was then processed into an ARMA model with the NN2TF algorithm. With an error rate of 1.43% to 4.34%, it showed that this method could be well accepted for modeling induction motors [19]. The mechanical parameters of the induction motor were investigated by the adaptive linear neuron (ADALINE) method. The two parameters found were moment inertia and viscous damping ratio [61]. Resistance parameters of the induction motor with 60 Hz, 220 V, 7.5 hp could be found using PSO and GA algorithm [62]. Those parameters were stator and rotor resistance R_s R_r, stator and rotor leakage-resistance x_1 x_2, and magnetizing resistance x_m. The induction motor modeling showed that the PSO and GA methods are realistic and reliable [24]. The rotor resistance was an AC motor parameter found by Elman Neural Network method. Good adaptability and a non-linear function approach were the main features of the proposed method. Good adaptability and high accuracy indicate that this method could be used properly for system modeling [21].

DC servo motor parameters which consist of K (sum of voltage displacement, torque, the gear), parameters a, b, c (in the 2nd order transfer function), were found by the PSO algorithm. The best parameters were obtained with the equation values K=0.4029, a=0.3920, b=0.7054, and c=0.0110. The final result showed a good value with an accuracy of 94% [10]. The DC motor research used the nonlinear autoregressive method with Exogenous (NARX) neural network input for system identification [63]. Several parameters obtained after the identification process are fit to estimation 95.78%, FPE = 8,498, and MSE 8,488.

A summary classification of the various methods used in motor identification was shown in Table II. This classification was ordered based on the method used started from the least square method to hybrid artificial intelligence. Several researchers have found motor parameters with transfer function (TF) some were more detailed in finding electrical parameters (EP) (electromagnetic force, resistance, inductance, current, voltage), mechanical parameters (MP) (damping ratio, friction, torque), and both of them (EMP).

IV. CONCLUSION

Identification of a motor system is very necessary because it will affect the control process. Two important motor parameters are electrical and mechanical. The parameters of the motor have been obtained with various identification systems, both conventional and more modern. For conventional methods such as the least square method, recursive least square, and some of their variation models, it is a simple method but has the advantages of fast processing and small memory. As for more modern methods such as using fuzzy logic, artificial neural networks, genetic algorithms, and PSO and some combinations of these methods have the advantage of being able to find complex and non-linear parameters. But this has to be paid for with a long processing time and required a lot of memory.

In fact, there has never been a perfect system identification that covers the entire system being sought. Mathematical model, signal sampling frequency, order model, are some system identification variables that need to be considered. Certain limitations occur in the identification of this system. Mastery and knowledge of the system being tested is an important factor in system identification.

TABLE II. MOTORS SYSTEM IDENTIFICATION CLASSIFICATION

Plant	*Method/Algorithm*	*Parameter Model*	*Ref*
BLDC	Least Square Algorithm	TF	[53]
AC Servo	Least Square Estimation	TF	[15]
IM	Iterative Least Square	EMP	[16]
BLDC	Recursive Least Square	EMP	[55]
BDC	Recursive Least Square	TF	[56]
SRM	Recursive Least Square	EMP	[14]
BDC	RLS Parallel Processing	TF	[17]
IM	Extrapolative Least Square	TF	[54]
BDC	ARX	TF	[18]
BLDC	ARX	TF	[23]
BDC	Linear Quadratic Regulator ARX	TF	[57]
IM	ARMA	TF	[58]
IM	ARMAX	TF	[19]
IM	Neuro-Fuzzy	TF	[20]
IM	ADALINE	MP	[61]
BDC	GA	EMP	[22]
DC Servo	PSO	EMP	[10]
IM	Model Reference Adaptive System	TF	[25]
IM	GA & PSO	EP	[62]
IM	HGAPSO	EP	[24]
IM	The charged system search (CSS), differential evolution algorithm , PSO, GA.	EP	[27]
BDC	Taylor Series	TF	[59]
BDC	NARX Neural Network	TF	[63]
IM	Extended Kalman Filter	EM	[60]
Stepper Motor	Extended Kalman Filter	EMP	[12]

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