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PARAMETERS ESTIMATION OF DC SERVO MOTOR USING DATA DRIVEN-MACHINE LEARNING BASED ESTIMATION APPROACH

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Abstract

Accurate machinery plays an important role in automotive industries. In the manufacturing landscape of accurate machineries, servo motors and drives are ruling the automation and robotic manufacturing industries. Also, the industry demands for the advancements in accurate control techniques of servo motor which is more powerful to meet the requirements. Due to depreciation and ageing effect, the parameters of DC servo motors change over time. As a result, it must be updated automatically. The characteristics of DC servo motors fluctuate with time as a result of depreciation and the ageing impact. It must therefore be updated automatically while the plant is operating. The system parameters estimation process with high preciseness of a DC Servo motor operating with highly nonlinear relationship is challenging. The estimation process has a significant impact on the accuracy of the controller parameter settings. For the DC servo system to operate well, it is crucial to estimate the precise parameters. This research suggests a data-driven machine learning estimation approach (machine-learning based regression) to address this issue and offer a reliable data base for developing the optimal control strategy for DC Servo motor. This study introduces parameter estimation of a DC servo system, which is used to obtain the precise and trustworthy estimation of parameters. The proposed strategy is easy to use and flexible, therefore it will produce results that are effective and efficient in terms of computing. The significance and effectiveness of the proposed methodology were underlined by contrasting its efficacy with that of the existing methods.

Keywords: DC Servo motor, Parameter estimation, Optimization technique, Data Driven Method, Machine Learning.

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Introduction

Industrial robots require accurate machinery with low tolerance levels to carry out their tasks, hence servo motors and drives are essential for successful operation [1]. Servo motors and drives are anticipated to continue growing in popularity as automation and robotic manufacturing become more prevalent across the manufacturing landscape. The primary end-use market for servo motors and drives is the automotive industry [2]. Multiple motors are present in modern vehicles, each serving a particular purpose. In automobiles, servo motors and drives are used in systems for anti-lock brakes, fuel injection, and cruise control. Furthermore, robots are widely used in automotive assembly lines for tasks including material handling, automated chassis assembly systems, and painting, among others. As automation technologies are adopted by the car sector to improve productivity, the logistics segment is also benefiting from the usage of automation solutions, which is enabled by servo motors and drives [3].

Basic electric motors controlled for a certain angular rotation by servomechanism are known as servo motors. They are used in a closed loop system that employs position feedback to control the rotational speed, and they include both AC and DC motors. Currently, large industrial applications that demand control typically use servo motors. They are used in remote-controlled toy cars, DVD and CD players, and many other aspects of daily life. Servo motors used in industrial environments have both speed and position sensors. They use derivative control algorithms (proportional-integral), which make it possible to swiftly position the engine since the speed of the shaft can be controlled. In order to generate motion that is proportional to the command signal, a servo drive receives a command signal from the control system, amplifies it, and then transmits the electric current to a servo motor. The command signal often denotes a necessary speed, although it can also denote a desired position or torque. The servo drive receives information about the motor state via a sensor that is linked to the servo motor. The servo drive compares the commanded motor state to the actual motor status. [4]

Due to its importance, industries are expecting to improvise its performance by introducing new technologies [5]. The advancements includes Machine Learning techniques applied for control systems like industry 4.0 applications [6] & multi robot task allocation system [7]. For various non-linear systems, the machine learning techniques were applied to obtain best control strategy [8]. Reinforcement learning approach is used for predictive control applications [9] and also for Speed Servo systems [10]

Due to depreciation and ageing effect, the parameters of DC servo motors change over time. As a result, it must be updated automatically. The physical parameters of the system affect controller parameter setting. Hence it is very important to estimate the accurate parameters for the successful operation of DC Servo system. Some parameters are constant, while others fluctuate over time, such as the torque constant (which is affected by magnetic influences) and the inertia J, which is affected by the presence or absence of loads on the rotary shaft. As the DC motor model exhibits a link between torque and current. The motor's shaft spins due to the torque, and we may relate this spinning to the back EMF (electromotive force). Shaft inertia, viscous friction (damping), armature resistance, and armature inductance make up the remaining characteristics. Although some of these quantities may have values provided by the manufacturers, those values are simply estimates. In order to determine whether our model accurately depicts the DC servo motor system, we need to estimate these characteristics as exactly as we can. Parameter Estimation provides various state-of-the-art estimation methods. The parameter estimation method for DC servo motor is already introduced. In which three methods were introduced and the results from each method were compared to select the best method. In which, the system identification technique utilized measured input and output parameter. To execute this technique, system identification toolbox can be preferred. But this technique lags accuracy when compared to parameter estimation technique using optimization method [11]. System identification can be done using Neural Network approach which uses data driven control method [12]. The data driven methods are used for prediction of control strategy in autonomous systems [13] , building energy management systems [14], wind farm's frequency regulation services [15], DC Motor [16], nonlinear tank systems [17] and for optimization problems [18] etc.,. In order to estimate the precise parameter values, data driven method is introduced in this paper. The data driven method [19] could make use of test data or first-principles math approach. In this paper, two methods of parameter estimation of DC servo motor were experimented and also proposed data driven based estimation technique by highlighting its significance when compared to other two methods. The section organization of the paper are as follows: Section 1 -Detailed Modelling of DC Servo system using Transfer function approach, Section 2-Parameter estimation methods- Comparing coefficient method, Parameter estimation Toolbox, Section 3-Introducing Data driven method-based Parameter estimation, Section 4-Conclusion

1. MODELLING OF DC SERVO SYSTEM USING TRANSFER FUNCTION APPROACH

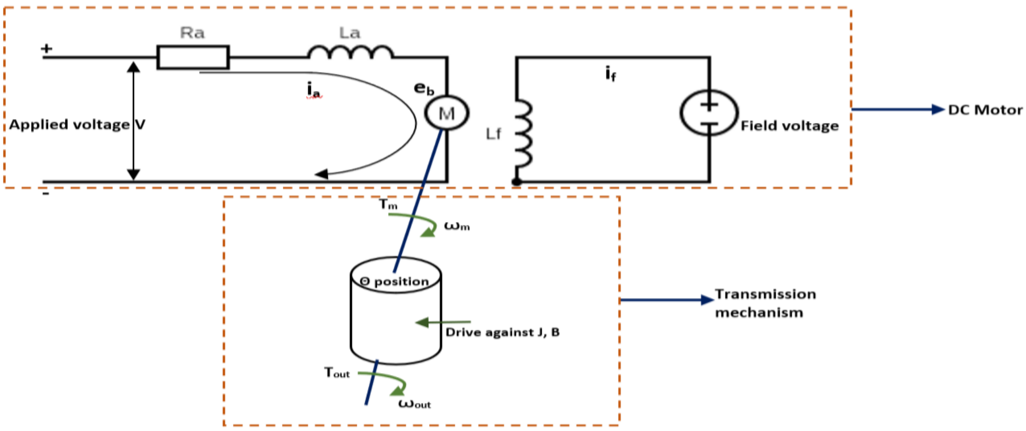
The advantages of modelling dynamic systems are well known to engineers and scientists across disciplines and industries.

The parameter details of DC Servo motor are mentioned as follows:

Parameter Abbreviation Units

- Moment of Inertia J_m Kg.m^2
- Back EMF constant K_b Volts/rad/sec = Torque Constant K_t N.m/A
- Frictional Constant D_m N.m/rad/sec
- Electric Resistance Ra Ohm
- Electric Inductance L_a H
- Load inertia J_d Kg.m^2
- Armature Current I_a Amps
- Angle of motor shaft θ rad
- Developed Torque T_d N.m
- Load Torque T_{load} N.m
- Back EMF E_b Volts
- Armature Voltage Ea Volts

In general, the circuit layout for DC Motor is mentioned as shown in below Figure 1:



Dynamic parameters of DC servo motor selected for the estimation process are Ra, La, Km, J, Jd & B_m. The DC Servo electrical and mechanical subsystem developed in Simulink as shown in Figure 2.

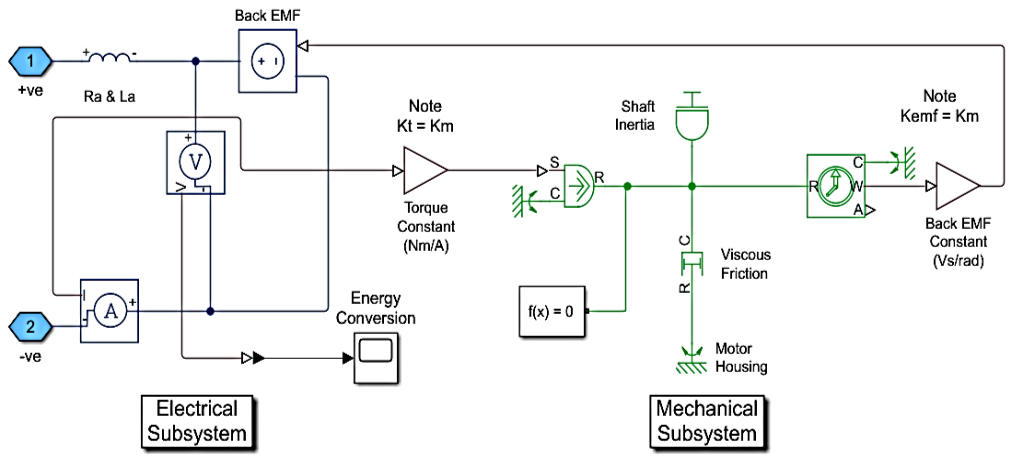


Figure 2 – DC Servo Electrical-Mechanical subsystem model-MATLAB Simulink

Formulation of Transfer function:

To build the whole servo system, the operational amplifier, attenuator, preamplifier and servo amplifier are used as signal pre-processing devices for providing the exact speed reference for the precise angle expected by the user. To facilitate the input voltage proportional to the input reference angle is achieved by the potentiometer connected in the input side.[20] [21] [22]

To measure the speed produced by the motor, the tacho generator is used. The voltage proportional to the measured speed is fed back for comparing with the input voltage. This whole mechanism is represented in Figure 3.

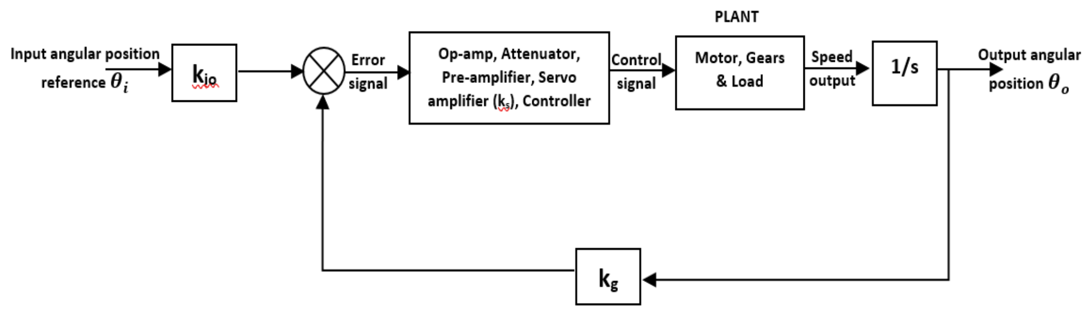


Figure 3 – Servo mechanism

For the servo system, the input reference angle $\theta_i(s)$ is given as input and the output angle obtained is $\theta_o(s)$.

The open loop transfer function of the motor in no load condition is given as,

$$G_o = \frac{\theta_o(s)}{V_a(s)} = \frac{k_t}{s\,[J_m s + D_m][R_a + sL_a] + k_t k_b}$$

OR

$$\frac{\omega_m(s)}{V_a(s)} = \frac{k_t}{[J_m s + D_m][R_a + sL_a] + k_t k_b}$$

By expanding the transfer function G_o (eqn 1)

$$G_o = \frac{\theta_o(s)}{V_a(s)} = \frac{k_t}{[J_m L_a]s^3 + [R_a J_m + D_m L_a]s^2 + \left[D_m R_a + {k_t}^2\right]}$$

The transfer function for the servo system is given as,

$$G_s = \frac{\theta_o(s)}{\theta_i(s)} = \frac{k_{io} \times k_s \times G_o \times \left[\frac{1}{s}\right]}{1 + [k_s \times G_o \times k_g]}$$

$$G_s = \frac{k_{io} \times k_s \times k_t}{s[[(J_m s + B_m)(R_a + sL_a) + k_t\, k_b\,] + k_t\, k_s\, k_g\,]} \times \left[\frac{1}{s}\right]$$

k_{io} → Gain of input output Potentiometer

k_{op} → Op-amp gain

k_{au} → Attenuator gain

k_{pu} → Pre-amplifier gain

k_{su} → Servo amplifier gain

k_t → Torque constant of motor

k_b → Back emf constant of motor

k_g → Gain of tacho generator

In order to obtain precise output from a plant, a system with precisely estimation parameters and proper control technique is necessary. The estimated parameters using best strategy shall be selected to test the accuracy of plant. The above mentioned transfer function shall be used with the advanced control techniques by using the parameters estimated from various approach to test the effectiveness of each method.

2. PARAMETER ESTIMATION METHODS

Parameter estimation methods are available for machineries like simple PMDC motors [23] and BAT Optimization algorithm is used for a parameter estimation of Robot with DC Servo Motor in a closed loop [24]. Most of the estimation technique used for DC Servo systems much complex and require huge computational cost which is not practically preferred for parameter estimation. In this paper, the Parameter estimation toolbox was selected as it is the most accurate method For DC Servo motor model parameter estimation.

METHOD 1- INDIRECT METHOD OF COMPARING COEFFICIENTS:

In this method, the system equations need to be formulated by understanding the relationship between various parameters of DC servo motor. Then the Transfer function of the DC servo motor to be derived. By comparing the denominator coefficients of the DC Servo motor transfer function with the denominator coefficients of the generic process model Transfer function, the parameters are estimated.

This method is easiest one but it lacks accuracy. The main reason is some parameters are assumed.

For this process, the simscape model of DC Servo subsystem (DCSS) is formulated and the input voltage applied to this DCSS; the measured output is motor shafts angular position.

In this method, the following parameters are estimated: the moment of inertia, Armature resistance, armature inductance, Back EMF constant, torque constant and Frictional constant. Before using this method for parameter estimation, the process model transfer function is obtained using transfer function approach.

In general, the process model transfer function of the third order system of the machine with electrical input and mechanical output system is represented as,

$$G_o = \frac{\theta_o(s)}{V_a(s)} = \frac{k}{s[\,1+\tau_1 s]\,[1+\tau_2 s]}$$

By expanding the above transfer function (eqn 2)

$$G_o = \frac{\theta_o(s)}{V_a(s)} = \frac{k}{s+\tau_1 s^2 \tau_2 s^2 + \tau_1 \tau_2 s^3}$$

By comparing the coefficients of equation 1 & 2,

$$\tau_1 \tau_2 = J_m L_a$$
$$\tau_1 + \tau_2 = R_a J_m + D_m L_a$$
$$1 = D_m R_a + {k_t}^2$$

The input voltage applied to the motor is 6 Volt. From the steady state value of current and speed, the electrical and mechanical time constants are obtained as 1.21ms and 18.4ms.

After finding Values of k, τ_1& τ_2, we can find numerical values of motor parameters by evaluating the above-mentioned equations.

The numerical values found from this method are as follows:

Jm = 12.27e $^{-3}$ Kg.m^2

Kt = 4.25 e − 3 (N.m/A)

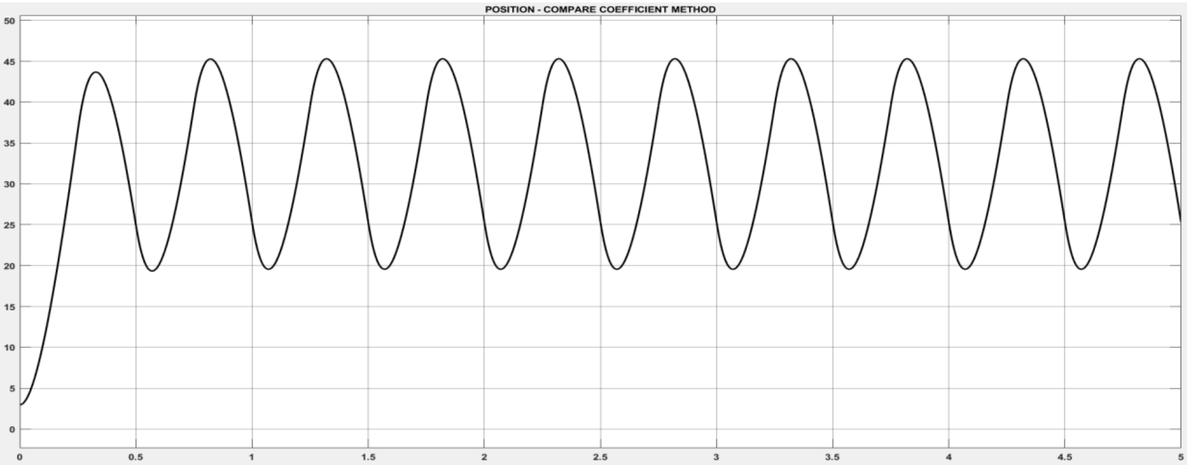
Dm = 0.67 (N.m/rad/sec)

Ra = 1.5 Ohm

La = 1.81e $^{-3}$ H

Ra value is assumed as the measured parameter as Resistance of DC Servo motor and this will be used to find other parameters. Accuracy of this method is obtained from the position output comparison between simulated value and reference value mentioned as follows:

The desired value of angle is measured as 50 degree. The measured value from this method that the curve trajectory is 45 degree. The simulation time is 5 second.



While comparing the parameter estimated with the desired parameters, the accuracy of this method is around 90 percent. So, the parameter estimation toolbox is used to track the desired curve with highest accuracy which uses Simulink optimization toolkit

METHOD 2: PARAMETER ESTIMATION TOOLBOX

Even though modeling and parameter identification using constraint optimization technique is available, the optimized solution with highest accuracy can be achieved using this parameter estimation toolbox.[25]

To converge optimized solution of Parameter, this method essentially uses data from collected tests as well as data from simulations. The model is then validated using data from live tests. In this technique, fundamental principles are utilized. In the first step of this process, measurements are really taken from a running DC servo motor. The following stage entails specifying the parameters to be approximated, beginning with a hunch. After that, the parameter values are approximatively estimated using the Parameter Estimation Toolbox in Simulink.

In actuality, measurable data is also loaded for model validation. The next step is to plot the measured and simulated data to determine how well they correspond to the data from the present DC Servo Motor. Model parameters must be re-estimated if the simulation does not match the measured data. Until estimate converges or finishes, the parameter estimation tool will iterate parameter values. The effectiveness of the estimating process can be demonstrated by plotting measured and simulated data together.

The chosen parameters are five. Constants of friction (D_m), moment of inertia (J_m), torque (K_t), inductance (L_a), and resistance (R_a). According to the datasheet for the DC Servo Motor, we set the initial values for these parameters. It also defines the range of these parameters from zero to infinity. Even the initial values couldn't able to meet the expected trajectory of angular position, this parameter estimation toolbox shall be used to optimize the parameters such that its meets the desired response after few iterations. The initial values of these parameters [11] are as follows:

Jm = 9.027e^{-3}

Kt = 4.943e^{-3} (N.m/A)

Dm = 0.518 (N.m/rad/sec)

Ra = 1.93

La = 2.348e^{-3}H

These values are updated for estimating parameters.

Moreover, experimental data can be loaded from comma-separated value files, Excel, MATLAB variables, and MAT files. The following step is to choose the parameters that will be used to estimate the DC Servo motor.

1. Open Parameter estimation block and plot the model response. Observe that the simulated data does not match with the measured data. So, the model parameters need to be estimated
2. Select parameters for estimation. Click select parameters in the parameter estimation tab. Now load the initial values of these parameters as shown above and update it
3. Now to estimate the data select experiments option in parameter estimation category and check estimation data. Now to monitor the estimation progress click add plot option. This progress uses parameter trajectory method. Click view tab to check the estimation tab and trajectory iteration plot in single window
4. Click estimate option in the parameter estimation category to start the estimation process.
5. Now the iteration takes place until the simulated data and measured data matches i.e., the estimation converges.

   We must validate our conclusions using additional test data sets that can be measured from the actual DC servo motor after finishing the parameter approximation.

Figure 4 displays the cost function minimization plot to illustrate how the algorithm is performing after each iteration until convergence. To evaluate the effectiveness of the machine learning model, a cost function is used. It is useless to use a machine learning model without the Cost function. To evaluate how well a machine learning model works, use the cost function. In essence, a cost function contrasts projected and actual values. A wise selection of the Cost function enhances the model's dependability and trustworthiness.

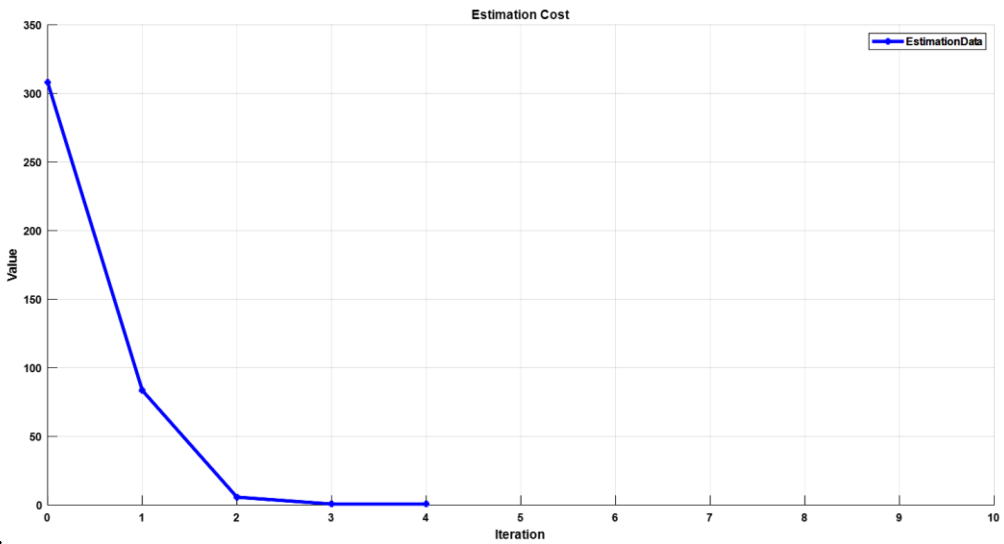


Figure 4- Cost function minimization plot

Figure 5 depicts the parameter trajectory map for the various parameters that need to be estimated in order to demonstrate how close they are to reaching their ultimate values

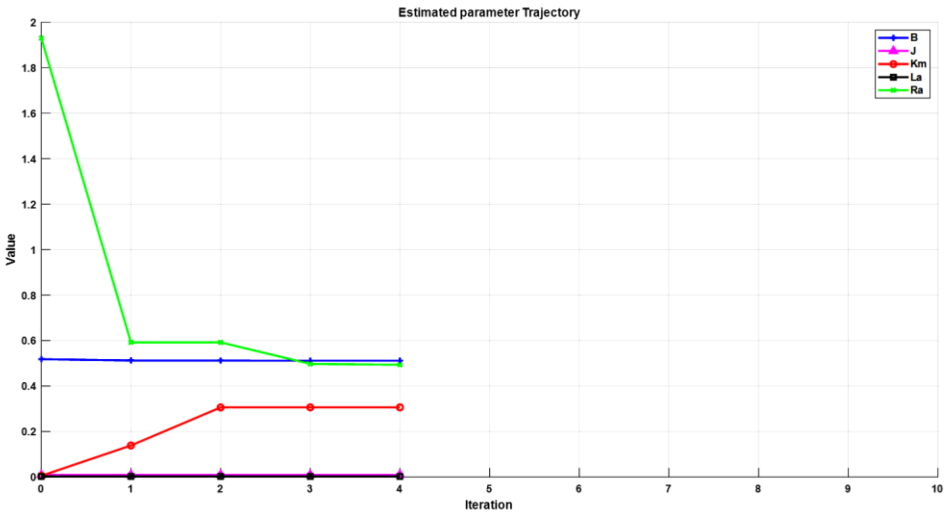


Figure 5- Estimated parameter trajectory

Figure 6 depicts the model fit plot of the estimated data versus the observed data, which demonstrates the technique's accuracy after a limited number of rounds. After using the training data to train the model, the estimated data converges with the desired data and fits with high accuracy after few iterations.

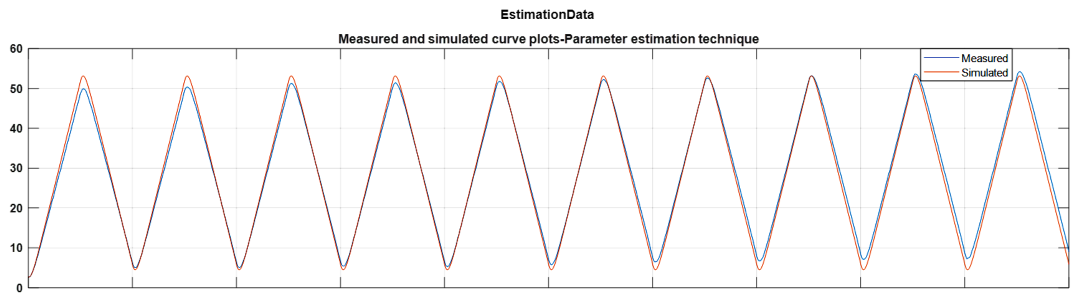


Figure 6- Convergence-Model Fit plot

For each iteration, the F count and the estimation data by minimizing the cost function to meet the objective is shown in table 1.

Table 1

Iteration	F-Count	Estimation Data (Minimize)
0	11	308.1377
1	22	83.5586
2	33	5.7234
3	44	0.7146
4	55	0.7033

The estimated parameters are as follows:

Estimation result(s):
B = 0.51141
J = 0.009751
Km = 0.30628
La = 0.0022769
Ra = 0.4937

An accurate prediction should match not just the experimental data set but also additional test data that was gathered from a real-world experiment. For this experiment, the Validation data set has already been loaded. The simulation findings show that the test dataset's model plot response closely resembles the simulated data. This method's results are around 99% more accurate than the real measurements, demonstrating its higher precision.

3. INTRODUCING DATA DRIVEN METHOD BASED PARAMETER ESTIMATION

The techniques used for parameter estimation are called estimators. Some estimators are: Probability Plotting, Rank Regression (Least Squares), Maximum Likelihood Estimation, Bayesian Estimation Methods [26]. But these estimators are not data driven.

This section suggests a data-driven machine learning estimation approach (machine-learning-based regression) for accurate parameter estimation for DC Servo motor parameters, which are challenging to monitor correctly due to their complicated nonlinear characteristics.

Model-based techniques estimate system parameters using a physics-based model. The benefit of this technology is that it is generalizable and thus applicable to various categories of machinery. Unfortunately, developing an accurate DC Servo system model across different operating areas is frequently difficult, and a lack of accuracy and precision impairs performance. With developments in sensing and computational capability over the previous decade, substantial volumes of data are now being captured during DC Servo system operations. Nowadays the system's dynamics can be easily identified using dynamical systems models from data [27]. Analysis of these massive amounts of data allow for analysis of the plant's performance in various modes of operation and under various environmental circumstances. Data-driven procedures, on the other hand, are situation-specific and computationally complex, both in terms of data pre-processing and analysis. Data-driven methods have received a great deal of attention in parameter estimate research, as they do not require a mathematical model of the plant.[28**]** In this section, the data driven method is introduced to estimate DC Servo motors' parameters. Many studies on various plants have demonstrated the potential application of data-driven, soft computing algorithms such as artificial neural networks, fuzzy logic, and neuro-fuzzy based methodologies for plant modelling and parameter detection.[29]. Nowadays the deep learning techniques were used for digital control systems and in which parameter estimation techniques shall be incorporated. [30]

In the proposed approach of data driven based parameter estimation, First, the actual data collected from the DC Servo motor during operation is processed to create the data module. Next, a large number of data sets are used for the machine learning model training that follows. To reduce the dimensionality of the data and the computational load, the Random Forest (RF) method is used for data set feature screening. Finally, the Generalised

Regression Neural Network (GRNN) is used. The precise estimation of the DC servo motor characteristics must be accomplished using a data-driven technique.

4. CONCLUSION

Although the conventional approach to comparing coefficients is straightforward, it does not produce accurate experimental results. When using the second technique with the parameter estimation toolbox, accuracy was at its highest. The parameter estimation approach based on the L-Method may operate with high consistency during the operation of the DC servo motor, which makes the data-driven way of machine learning technique ideal for estimation and accuracy. The T-Method then contains oscillations, which results in a somewhat substantial error in the estimation of the parameters. The L-Method will therefore provide better and higher estimation accuracy.

As a result, this method may provide a solid data base by precisely estimating the simulation parameters of DC servo motors, which also increases control precision.

Even if data-driven models produce accurate results, they often provide little understanding of the workings of the system. Future work could focus on experimenting this suggested strategy into practice in real time and introducing a way to get insight into the system's dynamics. Future work also may be using estimated parameters for the DC servo system simulation with advanced control techniques.

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