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Auto-Tuning PID Controller on Electromechanical Actuators Using Machine Learning

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Abstract

The performance of an electromechanical actuator largely depends on the control strategy implemented and calibrated. The purpose of this paper is to analyze the shortcomings of existing methods and practices involved in the manual tuning of a Proportional-Integral-Derivative (PID) controller of a Brushless DC (BLDC) motor and therefore, to propose an improved auto-tuning method. The controller investigated is a 3-stage cascaded PID, where the outermost loop is a position-based control followed by speed and current loops, respectively. The tuning method is independent of the application and provides a fast, stable, and efficient response. The motor model is first approximated to a first-order system; then mechanical parameters of the motor such as inertia and coefficient of friction are estimated using the Recursive Least Square (RLSQ) optimization method. These mechanical parameters are used in conjunction with the steady state gain and time constant of each control loop to calculate PID gain. To further improve the performance of the controller, the load torque on the motor is also estimated using an Artificial Neural Network (ANN), which is used as a feed-forward command in the current controller to improve the response of the system. The tuning method was tested on an actuator which consisted of a BLDC motor and a gear reducer. The neural network was developed by taking extensive data on the brake fixture setup. The actuator was subjected to different loads and speeds irrespective of the application load profile. The PID gains for the actuator were then calculated using the tuning rules by running the actuator on the actual application. The results demonstrate a 90% improvement in overshoot, 45% in settling time, and a 12% improvement in current consumptions against the initial baseline manual calibration.

Introduction

Automobile manufacturers consistently try and introduce new technology which aims at improving the comfort and safety of the end users. In such a competitive market, a small feature can influence the customer. Actuators are an integral part of automobiles, enabling feature automation and aiding comfort and safety features. A modern passenger vehicle is equipped with more than 100 such actuators for various applications ranging from Heating, Ventilation, Air -Conditioning) HVAC systems, transmission control, seat adjustment, and headlight positioning, among others [1]. With a shift towards autonomous vehicles, this number is set to increase considering the safety requirements associated with such vehicles.

This rising demand for automation will see an increase in the actuator market size and open the doors for actuator manufacturers to innovate and make actuators more efficient and reliable. Lower noise and vibration, compact and lightweight design, reliable and repeatable performance, and the ability to install in tight spaces will be some of the driving factors for innovation.

Amongst different actuators available on the market, the electromechanical actuators check all the above boxes by achieving low noise operation and delivering high torque/power density. Such actuators are becoming increasingly popular in x-by-wire technology, wherein the actual mechanical component and linkages are replaced by electrical or electro-mechanical systems, Shift by wire and Steer by wire are some examples [2, 3]. Electromechanical actuators consist of an electric motor and gear reducer for torque multiplication. In some cases, it may also consist of additional electronics which control the motor instead of an external controller, making it a smart actuator. Since these actuators are replacing the actual mechanical components in some cases, the safety and performance requirements are of utmost importance. One of the key considerations for actuator manufacturers is to design a product that can be used as an off-the-shelf solution i.e., a single product that can be easily integrated into the existing system with the ability to customize based on customer's needs. This helps manufacturers to market their products for different applications with minimal changes. The challenge with this approach is to work on a universal robust solution without making it expensive. For example, the controller of a smart actuator needs to be calibrated based on the customer's application and load profile. This can be a time-consuming activity if manually done or if the system dynamics are unknown.

The controller type discussed in this paper is the classic PID controller. PID stands for proportional, integral, and derivative. These three control gains influence the controller output. P terms increases the control output by increasing it proportionally to the error between desired setpoint and actual feedback from the plant. Similarly, the I term integrates the error over time, and the D term estimates the future error based on its current rate of change.

There are multiple methods available in the literature to calculate the gain values of the PID controller but need manual effort. One of the manual tuning methods for PID is shown in Table 1, this is known as the Zieglar-Nichols method [4]. It is performed by increasing the proportional gain to K_u until the output of the control loop is stable but has consistent oscillations with the time period T_u. PID control values are then using the following table.

TABLE 1 Ziegler Nichols Method

Control	K_p	T_i	T_d	K_i	K_d
P	$0.5K_u$	-	-	--	-
PI	$0.45K_u$	$0.83T_u$	-	$0.54K_u/ T_u$	-
PID	$0.6K_u$	$0.5T_u$	$0.125T_u$	$0.12K_u/ T_u$	$0.075K_u T_u$

The focus of this paper is to investigate a method that aims at eliminating the need for manual tuning of the PID controller for an unknown load on the actuator. The electromechanical actuator utilized in this paper consists of a brushless DC motor (BLDC), a two-stage gear reducer, and integrated electronics to control the actuator.

In the previous studies, auto-tuning methods are developed in a controlled method and focus on optimizing the controller gain parameters, whereas, in the present study, the system parameters such as friction, inertia, and load torque on the actuator are estimated to compute gain parameters. Parameters are estimated using recursive least square optimization (RLSQ) and artificial neural network (ANN)

Methodology

The discussed method was established using a smart actuator, developed for automotive applications. One of the applications, and used for this paper, is an electronic transmission range selector, which is a shift-by-wire electronic shifter. The actuator replaces a conventional shift lever which enables the driver to shift transmission between the Park, Neutral, Reverse and Drive. The shift mechanism is discussed as a part of this paper considering the confidentiality. The actuator receives an electronic transmission range selection command and uses a BLDC motor to shift from the existing range to a new range requested by the driver. BLDC motor controller is implemented using a cascaded closed-loop method as shown in Figure 1. The

FIGURE 1 Cascaded Control Loop

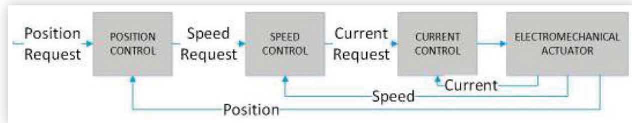
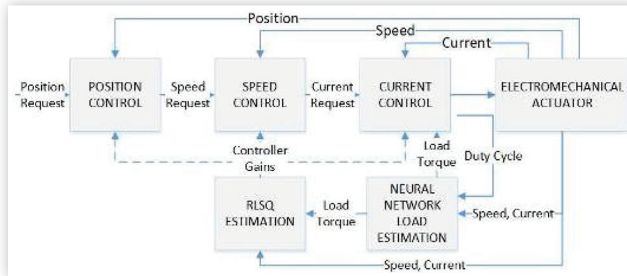


FIGURE 2 Proposed solution with two additional routines



controller consists of an outermost position loop, followed by a speed and an innermost current loop. The maximum torque generated by the BLDC motor is not significant and therefore amplified using a two-stage gear reduction. When a new range selection request is received by the actuator, the controller commands a corresponding position on the actuator. The outermost position loop calculates the speed required for the inner speed-loop to complete this shift using a proportional gain $\boldsymbol{k_{p,p}}$. Similarly, the speed-loop calculates the current required for the innermost current-loop to overcome any disturbances or load on the motor to attain the requested speed and complete the shift. Speed loop uses proportional and integral gains, $\boldsymbol{k_{p,s}}$ and $\boldsymbol{k_{i,s}}$ respectively. The performance of the actuator largely depends on the values of the gains mentioned above. Since the controller uses a cascaded loop approach, the gain selection, or the calibration process, becomes a challenge, and involves significant effort and time. Furthermore, the gain values selected for a given application might not have the same performance for a different application or customer due to different load requirements for example. This leads to manual calibration for every new application.

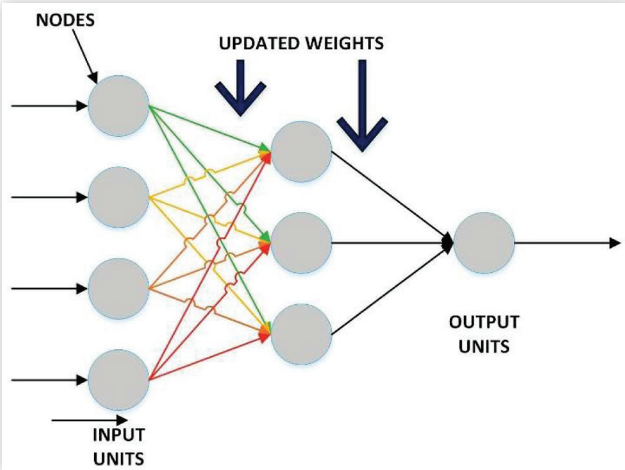
The proposed solution addresses these limitations and provides a solution that not only eliminates the efforts required to calibrate but also improves the performance of the actuator. As shown in Figure 2, two additional features are introduced to the existing control strategy.

First is to estimate the load torque observed by the actuator and the second is to estimate the system parameters which enables the required gain.

Load Estimation

The load estimation routine uses a trained artificial neural network (ANN) model to estimate the load observed by the actuator [5]. A neural network composes of nodes, connections of which are modeled as weights. Figure 3 illustrates the training method for an ANN. As can be seen from the figure,

FIGURE 3 Artificial Neural Network (ANN)



we need input parameters and output parameters for our training data. In this case, Motor Speed, Motor Current, and Motor Duty Cycle are used as input and Motor Torque is the output of the ANN. Since there is a gear reduction between the motor and torque transducer, the actual value recorded from the transducer is divided by the gear ratio to obtain motor torque.

As shown in Figure 3, the node receives the data and multiplies it by the associated weight and then adds the resulting products together and passes it to the outgoing connection by applying an activation function. These "weights" are calculated by training the net using Levenberg-Marquardt optimization The weights are adjusted until we haven't completed the minimum number of optimization iterations and found the minima of the function, which is the mean squared error between the actual value and estimated values. The resulting estimated values are acceptable if the estimated value is within ±10% of the actual value. This acceptance criteria is constrained based on the application. The training process is demonstrated in Figure 4.

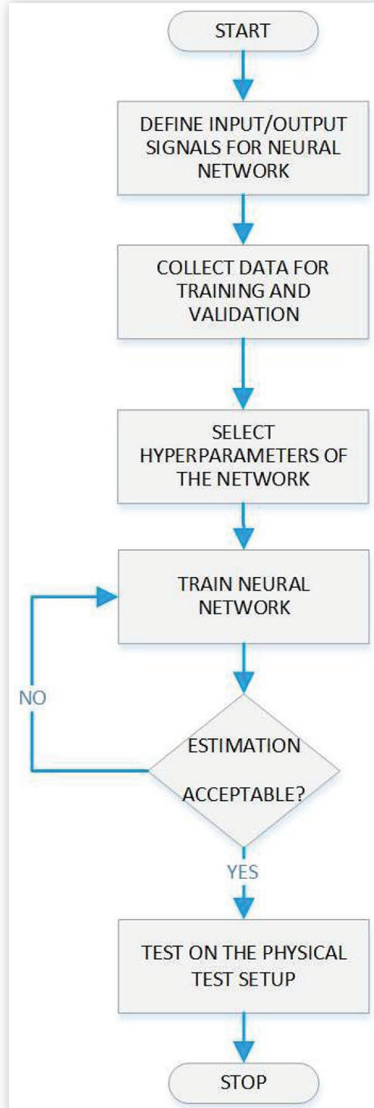
These nodes, activation functions, and layers in the ANN are known as the hyper-parameters. Hyper-parameters are optimized using Bayesian Optimization along with Levenberg-Marquardt Optimization to find the best size and configuration of the ANN [6].

A load observer [7] can also be used to estimate the load on the motor. An observer is an algorithm that combines feedback from the sensor with other information about the control system to produce observed feedback signals that are more accurate and reliable than the basic feedback signals. But the reason behind using ANN to estimate the load was to use the black box approach which also considers the non-linearities of the system which might be difficult to achieve using the load observer.

Tuning Rules

The tuning rules are mathematical formulas derived from the system's mathematical equation represented as a first-order equation as [8],

FIGURE 4 Artificial neural network (ANN) training method



$$Jk_\tau^{-1}\frac{d\omega}{dt}+k_f k_\tau^{-1}\omega+k_\tau^{-1}\tau_l = I \tag{1}$$

Where, ω is the motor speed, i is the motor current, τ_l is the motor load. J is the system inertia, k_f is the linear friction coefficient, and $k_\tau i$ is the electromagnetic torque generated by the motor.

In Laplace domain, the continuous time system resembles a low pass filter with time constant τ and steady-state gain K:

$$\frac{\Omega(s)}{I(s)}=\frac{K}{\tau s+1}, \tag{2}$$

Where, $K=\frac{k_\tau}{k_f}$, and $\tau=\frac{J}{k_f}$.

Using the estimated time constant and steady state gain, the control loop can be tuned based on:

$$k_{i,s}=\frac{4k_f}{T_{speed}};\quad k_{p,s}=\frac{4J}{T_{speed}} \tag{3}$$

FIGURE 19 Manually Tuned Gains: Complete Shift Sequence

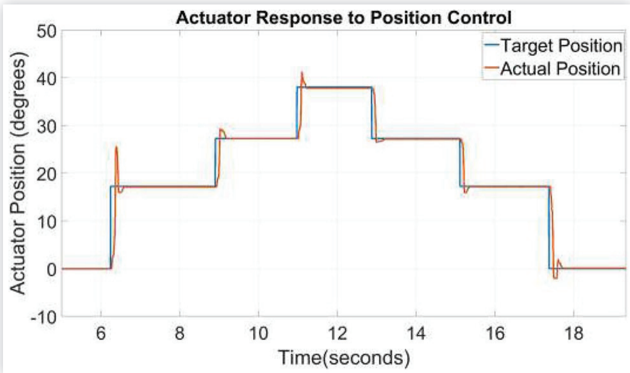


FIGURE 20 Auto-Calibration Method: Complete Shift Sequence.

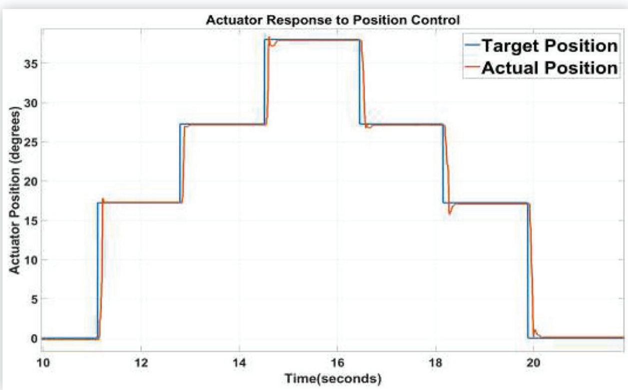


TABLE 3 Result Summary for Shift Sequence P to R

Control Structure	Overshoot	Settling Time	RMS Current
Manually Tuned Gains	~8 deg	320ms	18.60 A
Discussed Method: Feed Forward with Auto Cal Gains	~1 deg	210ms	16.37 A
% Improvement	**~ −90%**	**~ −45%**	**~−12%**

Conclusions

Compared to the traditional tuning method, the proposed auto-calibration method shows significant improvement in key areas such as rise time, settling time, and overshoot. Resource consumption for this method is inconsequential and has no negative effect on system throughput. The feed-forward torque control estimates the load on the actuator and provides a pre-emptive current to the motor to overcome the torque during a shift command. The load estimation ANN algorithm was also tested on an actuator that has gone through end-of-life testing and the results were satisfactory and within the +/- 10% range. The cascaded PID controller provides a corrective action by using new gains calculated by using motor system parameters. When tested on the transmission range shift application, this method can eliminate the need for manual tuning and thereby save engineering hours. Moreover, the auto-calibration method eliminates the need for gain scheduling in a PID controller.

However, considering the black box approach used for load estimation, it is important to limit the pre-emptive current provided to the actuator to prevent any undesired behavior. To further improve the performance, additional parameters like motor temperature, actuator's capability to back drive, etc. for the estimation of load torque will be considered.

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Definitions/Abbreviations

ANN - Artificial Neural Network
BLDC - Brushless Direct Current
CAN - Controller Area Network
HVAC - Heating, Ventilation and Air-Conditioning
PID - Proportional-Integral-Derivative
RLSQ - Recursive Least Square

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