Iterative Approach for Parameter Estimation in DC Motor Based Motion Systems

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***Abstract*—Accurate parameter estimation of small scale DC motors is a challenging and a complex task compared to it's large scale counterpart. This research proposes a novel technique of parameter estimation based on the disturbance observer and optimization algorithms for DC motor applications.A simplified yet an accurate cost function has been proposed for the model which is based on the disturbance observer (DoB) . Newton Raphson algorithm is used as the optimization algorithm. Moment of inertia, static friction, and coefficient of viscous friction are estimated and compared with the actual parameters. Simulations were carried out to justify the approach. The novel parameter estimation technique has shown accurate results compared to the existing methods.**

***Index Terms*—Parameter estimation, Newton Raphson, Disturbance observer (DoB), Cost function, Least square error, Moment of inertia, Static friction, Viscous friction**

I. Introduction

DC motors play an important role in mechanical motion systems. In the early days, majority of DC motor applications were limited to large scale systems such as in automobile industry and in manufacturing industry [1], [2]. Recent achievements in technology such as high speed digital processors and high resolution motor drivers have broaden the application range of motion control systems [3].

High accuracy and robustness are crucial factors of precises motion control applications [4]. The achievable accuracy/precision of a motion control system is bounded by sensor limitations [5]. As an example, the maximum achievable accuracy of an encoder is bounded by the encoder resolution. Robustness is an integration of both stability robustness and performance robustness. Having a high robustness reduces the fine tuning efforts in motion systems against the uncertainties. Thus for a precise motion requirement, it is necessary to achieve high performance in both mechanical and electrical aspects [3], [6].

System modelling is a decisive aspect in a motion control system design. However, modelling uncertainty is a major barrier in motion control systems [7]. Modeling uncertainties can deteriorate control performances. Unexpected operation or even system instabilities can cause as a result. As per the Literature, modelling uncertainties consist of structured uncertainties and unstructured uncertainties [7]–[11]. Structured uncertainties are caused by unknown parameters within the known model and the unstructured uncertainties are the unmodeled nonlinearities [7]. Researchers have proposed several control architectures to minimize the effects of these uncertainties. Generalized internal model control and Disturbance observer (DoB) based control models are some popular examples [12]. Particularly, DoB model proposed by Ohnishi et al is the most prominent robust control tool since the robustness can be altered according to the user's choice [13]. The DoB estimates system uncertainties and disturbances, which are then fed back using an inner loop to accomplish the robustness [14]. The performance goals are achieved through an outer loop by considering only the nominal plant model [12]. Design parameters of DoB such as inertia and motor thrust constant are prone to structured uncertainties [6]. Therefore, use of DoB in precise motion control applications is still a challenge. The requirement of knowing exact system parameters is therefore an important aspect in motion controller designs [4].

The manufacturer given data is considered as the system parameters in most of the DoB based DC motor applications. However, literature claims these values are inaccurate due to several reasons [4]. Wear and tear effects,addition or removal of additional accessories to the shaft, and estimation errors of manufacturers are some common reasons. Therefore the use of parameter estimation methods are popular among motion control applications. Constant velocity test for frictional coefficients, and acceleration/deceleration tests for inertia estimation are some of the widely used techniques. Small scale motion systems require high levels of estimation accuracy to meet the performance goals than the large scale systems. Achieving such accuracy requires a huge amount of resources such as processing power and time. Inaccurate estimations could lead for undesired operations in motion control systems.

Ubiquitous advancement in computational power of digital processors, researchers have focused on more intelligent and advanced models that use techniques like regression, for parameter estimation [15]–[20]. Use of machine learning algorithms such as gradient descent and newton raphson methods have shown improved accuracy and reduced effort in this context. In practice, a selected regression model consists of partially known and partially unknown components. Furthermore, the structural model of the system is to be known and a prior knowledge on known components are required.

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A recursive optimization method is then used to estimate the unknown components.

In this research work, a novel parameter estimation method is proposed for the DoB based robust control models. This method uses modified newton raphson method which is an optimization algorithm combined with the DoB model and it has shown that this approach has better results compared to the conventional methods.

The paper is organized as follows. Section 2 gives the detailed DC motor model and introduces the disturbances acting on a motor. The DoB model for the DC motor is presented in section 3. Section 4 explains the regression algorithm for parameter estimation and thereby an objective function for optimization is proposed. The effectiveness of proposed method is revealed in section 5 through simulation results. Finally, section 7 presents the conclusion.

II. Disturbance Observer (DoB) for a DC Motor

A. DC motor model

The electrical model of a DC motor is presented in figure 1 [21]. The relationship between supply voltage, generated motor torque, and armature current can be formulated as in equations (1),(2),(3)and (4).

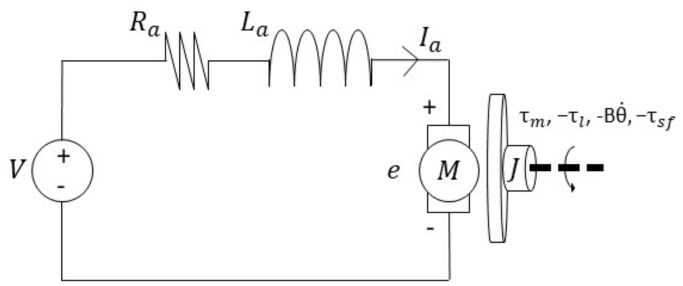


Fig. 1: Electrical representation of a DC motor

$$V = R_a I_a + L_a \frac{dI_a}{dt} + e \tag{1}$$

$$e = k_e \dot{\theta} \tag{2}$$

$$\tau_m = k_t I_a \tag{3}$$

Considering the dynamic parameters of the motor, generated motor torque (τ_m) can be re-written as in equation (4)

$$\tau_m = J\frac{d\dot{\theta}}{dt} + \tau_f + \tau_l \tag{4}$$

Here "$J\frac{d\dot{\theta}}{dt}$" term represents the torque due to the inertia of the system. As per the disturbance definition, disturbance applied on the motor shaft can be defined as in equation (5). Equation (4) is then can be reduced to equation (6)and (7). According to equation (7) the disturbance acting on a DC motor can be modelled as in figure 2.

$$\tau_{dis} = \tau_f + \tau_l \tag{5}$$

TABLE I: Nomenclature

Symbol	Description
V	Supply voltage
R_a	Armature resistance
L_a	Armature inductance
I_a	Armature current
e	Induced back-emf
k_e	Back - emf constant
$\dot{\theta}$	Angular velocity of the motor
τ_m	Generated motor torque
τ_f	Torque due to friction
τ_{sf}	Torque due to static friction
τ_{df}	Torque due to dynamic friction
τ_l	Torque due to external loads
k_t	Torque coefficient
k_{tn}	Nominal value of torque coefficient
J	Motor inertia
J_n	Nominal value of motor inertia
g_{dis}	Cut-off frequency of the low pass filter
B	Coefficient of viscous friction

$$\tau_m = J\frac{d\dot{\theta}}{dt} + \tau_{dis} \tag{6}$$

from equation (3);

$$k_t I_a = J\frac{d\dot{\theta}}{dt} + \tau_{dis} \tag{7}$$

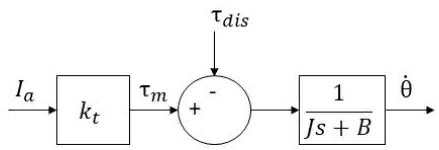


Fig. 2: Block diagram of a DC motor

B. Disturbance Observer(DoB) Model

In control theory, a disturbance observer is used as a robust control tool to enhance the overall system performance [22]. The basic idea of the DoB is to estimate disturbances and then compensate them [21], [23], [24].

The control strategy based on acceleration control is widely used in high precision applications due to it's simplicity and guaranteed robustness properties [25]. Motor model represented in figure 2 can be rearranged as in figure 3 to realize the acceleration control. It is assumed that viscous effects are as disturbances to the motor [26].

In case, where τ_{df} is the torque due to viscous friction and it can be expressed as in equation (8).

$$\tau_{df} = B\dot{\theta} \tag{8}$$

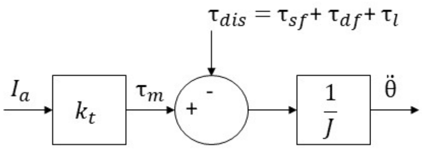


Fig. 3: Block diagram of a DC motor based on disturbance definition

As per figure 3, the disturbances on the motor can be estimated from equation (9). Since the nominal parameters can slightly be varied from actual values, the disturbances which are estimated from disturbance observer can be expressed as in equation (10).

$$\hat{\tau_{dis}} = k_{tn}I_a - J_n\ddot{\theta} \tag{9}$$

$$\hat{\tau_{dis}} = (J - J_n)\ddot{\theta} + B\dot{\theta} + \tau_{sf} + \tau_l + (k_{tn} - k_t)I_a \tag{10}$$

Figure 4 represents a disturbance observer integrated to a DC motor model, which is described in equation (9). Low pass filter $Q(s)$ is used to eliminate high frequency disturbance components caused by the measurement noise.

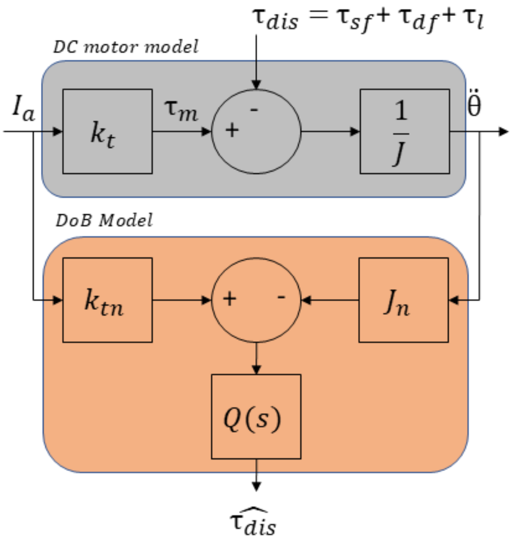


Fig. 4: DoB integrated DC motor model

$$\hat{\tau_{dis}} = Q(s)(k_{tn}I_a - J_n\ddot{\theta}) \tag{11}$$

where;

$$Q(s) = \frac{g_{dis}}{s + g_{dis}} \tag{12}$$

Due to practical drawbacks in measuring $\ddot{\theta}$, Ohnishi *et al.* had rearranged the model in figure 4 to the model in figure 5 which uses $\dot{\theta}$ as a measuring parameter [3], [14].

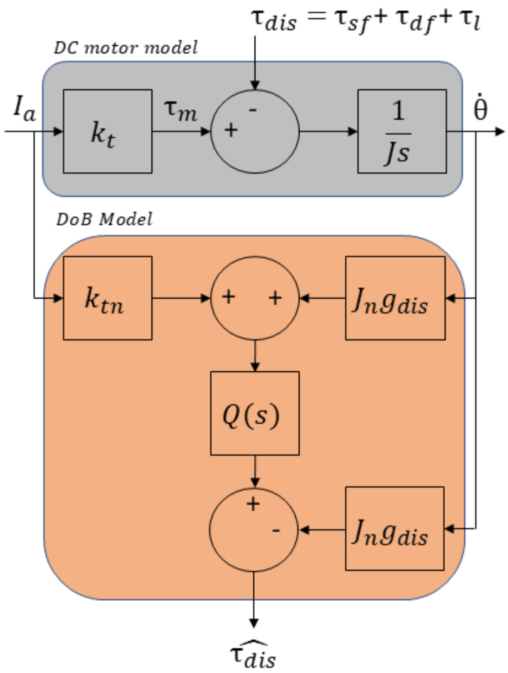


Fig. 5: Modified DoB integrated DC motor model

The disturbance observer presented in figure 5 estimates and feed-backs the uncertain disturbances to realize robustness. The effectiveness of disturbance estimation relies on several factors such as CPU speed, accuracy of estimated motor parameters, and the value of the filter constant g_{dis}. Next section will focus on a novel parameter estimation method to improve the accuracy of nominal motor parameters.

III. Linear Regression Model

This section is focused on deriving a linear regression model that relates the system parameters and motion parameters to the DoB estimation. It follows the equation (10). At the end of this section,it will be concluded that the problem of system parameter estimation can be reformulated to a problem of parameter estimation in a linear regression model.

The general form of a multi-variable linear regression model can be presented as equation (13) [27], [28].

$$y(k) = a_0x_0(k) + a_1x_1(k) + a_2x_2(k) + ... + a_nx_n(k) \tag{13}$$

The vector form of equation (13) can be expressed as in equation (14)

$$y(k) = X(k)A \tag{14}$$

where,

$$X(k) = \begin{bmatrix} x_0(k) & x_1(k) & x_2(k) & ... & x_n(k) \end{bmatrix} \tag{15}$$

$$A^T = \begin{bmatrix} a_0 & a_1 & a_2 & ... & a_n \end{bmatrix} \tag{16}$$

$y(k)$ - measured output
$X(k)$ - Vector of measurable motion quantities
A - Vector of unknown parameters

k represents the data point at time kdt where dt is the sampling time interval. Since the motor parameters are unique, a linear regression model is selected which makes the estimation process much more precise.

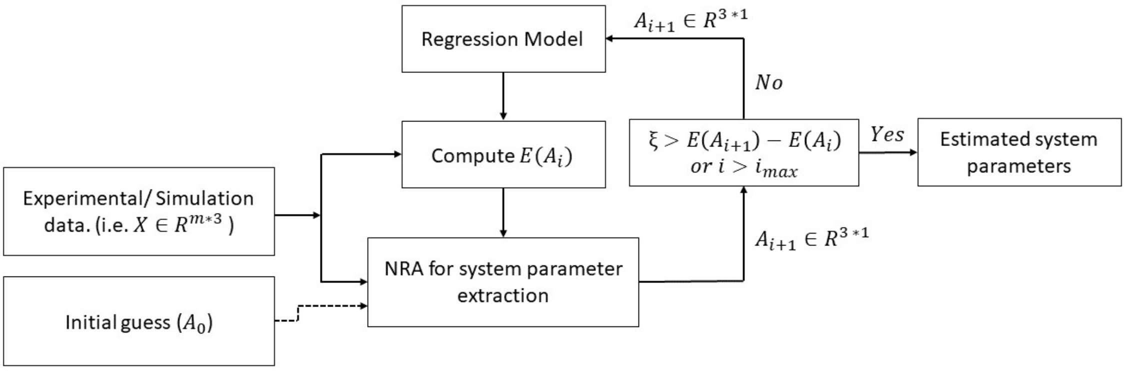


Fig. 6: NRA based iterative approach for parameter estimation

A. Problem formulation

Generally torque constant of a motor is constant over time compared to other motor parameters. Therefore, complexity of the derived motor model can be reduced by neglecting the variation of motor torque constant $\triangle K$. Hence, equation (10) can be reduced to equation (17).

$$\hat{\tau}^{e}_{dis}(k) = \triangle J\ddot{\theta}(k) + B\dot{\theta}(k) + \tau_{sf} \tag{17}$$

where $(J - J_n)$ = $(\triangle J)$ and $(k_t - k_{tn}) \approx 0$.

Angular velocity ($\dot{\theta}$) and angular acceleration ($\ddot{\theta}$) are measurable variables. Thus, the prediction of Disturbance observer output can be realized, if the coefficients $\triangle J$, B and τ_{sf} are known. The aim of this approach is to fit these unknown coefficients in a way such that the disturbance observer output coincides with the prediction of the model represented in equation (17).

For the ease of formulation purpose, equation (17) is rearranged as in equation (18).

$$\hat{\tau}^{e}_{dis}(k) = \begin{bmatrix} 1 & \dot{\theta}(k) & \ddot{\theta}(k) \end{bmatrix} \begin{bmatrix} \tau_{sf} \\ B \\ \triangle J \end{bmatrix} \tag{18}$$

Note that the equation (18) is of the form described in equation (14),

$$X(k) = \begin{bmatrix} 1 & \dot{\theta}(k) & \ddot{\theta}(k) \end{bmatrix} \tag{19}$$

$$A^T = \begin{bmatrix} \tau_{sf} & B & \triangle J \end{bmatrix} \tag{20}$$

Where, x_0 = 1, x_1 = $\dot{\theta}(k)$, x_2 = $\ddot{\theta}(k)$, a_0 = τ_{sf},a_1 = B and a_2 = $\triangle J$.

Therefore, it is clear that the system parameter estimation can be realized from parameter estimation of the linear regression model presented in equation (18).

B. Objective / Loss function

Least square error approach is simple yet a powerful numerical method in mathematics for optimization problems. The unknown variables of the model represented in equation (18) can be computed using an iterative approach by minimizing the square error $E(A_i)$ which is formulated in equation (21). Here, i represents the i^{th} iteration of the optimization process. The square error function which is described in equation (21) and (22) is the objective function or the loss function . It will be optimized in the next section to compute the unknown parameter matrix A.

$$E(A_i) = \frac{1}{2m}\sum_{k=1}^{m}(\tau_{\hat{dis},k} - \tau^{e}_{dis,k})^2 \tag{21}$$

substituting from (22);

$$E(A_i) = \frac{1}{2m}\sum_{k=1}^{m}(\hat{\tau}_{dis,k} - (a_0x_{0,k} + a_1x_{1,k} + a_2x_{2,k}))^2 \tag{22}$$

Here, m is the number of data samples and $x_{1,k}$ is the k^{th} reading of angular velocity / $\dot{\theta}(k)$ used in the estimation process.

IV. Model Fitting for Parameter Estimation

System parameter estimation of a DC motor can be achieved by solving the regression model which was derived in the previous section. In this section, a novel algorithm for parameter estimation is presented.

A. Newton Raphson Algorithm (NRA) for Least Square Error estimation

An optimization is performed to find the best matching solution for a pre-defined problem. Usually, this is achieved in an iterative manner. The selection of optimization algorithm is determined after considering various factors such as linearity of the task, influencing constraints and number of unknown parameters.

Gradient descent, steepest descent, and Levenberg–Marquardt methods are some of the widely used optimization algorithms [29]. However, they have several drawbacks such as computational costs, solutions not being the optimal local minimum and high sensitivity to noise.

This section presents a novel system parameter estimation technique based on NRA. This specific choice of optimization algorithm overcomes the previously mentioned drawbacks.

Furthermore, a rapid convergence can be achieved. Hence, NRA allows the implementation of a parameter estimation method which is suitable for real time applications.

The NRA is a powerful iterative technique used to solve algebraic equations. Initialized with an initial guess, an optimum solution can be attained by improving the guess until a tolerable error measure is achieved. The increment is computed using a series of second order Taylor expansions of $E(A_i)$ around the iterates. The second order Taylor expansion of $E(A_i)$ around A_i can be formulated as in equation (23) [30].

$$E(A_i + \triangle A) \approx E(A_i) + \nabla E(A_i)\triangle A + \frac{1}{2}\nabla^2 E(A_i)(\triangle A)^2 \tag{23}$$

The next iterate, A_{i+1} is defined in such a way that the quadratic approximation of $\triangle A$ is minimized. Then the iterate A_{i+1} is calculated as in equation (24).

$$E(A_{i+1}) = E(A_i) + \triangle A \tag{24}$$

The quadratic approximation is a convex function of $\triangle A$ so as to exists a minimum. This minimum is achieved by setting the derivative to zero as described in equation (25).

$$\frac{d}{d(\triangle A)}(E(A_i) + \nabla E(A_i)\triangle A + \frac{1}{2}\nabla^2 E(A_i)(\triangle A)^2) = 0 \tag{25}$$

Simplifying (25), equation (26) can be derived.

$$\nabla A_i + \nabla^2 A_i(\triangle A) = 0 \tag{26}$$

Therefore, the recursive term in NRA can be derived as in equation (27).

$$A_{i+1} = A_i - \nabla^2 A^{-1}\triangle A \tag{27}$$

Here, $\nabla^2 A_i$ is the hessian matrix of A_i and the $\triangle A$ is the gradient matrix of A_i. These two matrices can be described as in equation (28) and (29).

$$\nabla^2 A_i = \begin{bmatrix} \frac{\partial^2 E(A_i)}{\partial a_0^2} & \frac{\partial^2 E(A_i)}{\partial a_0 \partial a_1} & \frac{\partial^2 E(A_i)}{\partial a_0 \partial a_2} \\ \frac{\partial^2 E(A_i)}{\partial a_1 \partial a_0} & \frac{\partial^2 E(A_i)}{\partial a_1^2} & \frac{\partial^2 E(A_i)}{\partial a_1 \partial a_2} \\ \frac{\partial^2 E(A_i)}{\partial a_2 \partial a_0} & \frac{\partial^2 E(A_i)}{\partial a_2 \partial a_1} & \frac{\partial^2 E(A_i)}{\partial a_2^2} \end{bmatrix} = \frac{1}{m} X^T * X \tag{28}$$

$$\nabla A_i = \frac{1}{m} \begin{bmatrix} \sum_{k=1}^{m} (\hat{\tau}_{dis,k} - \sum_{j=0}^{2} a_j x_{j,k}) x_{1,k} \\ \sum_{k=1}^{m} (\hat{\tau}_{dis,k} - \sum_{j=0}^{2} a_j x_{j,k}) x_{2,k} \\ \sum_{k=1}^{m} (\hat{\tau}_{dis,k} - \sum_{j=0}^{2} a_j x_{j,k}) x_{3,k} \end{bmatrix} \tag{29}$$

where X is the "m" by 3 matrix that contains all the measured data. As a summary to the described algorithm, figure 6 illustrates the estimation of system parameters of a DC motor using NRA.

V. SIMULATION

To reveal the performance and feasibility of the proposed technique, computer simulations have performed using a programming platform. It has considered for the simulation purpose, a typical DC motor controlled by a conventional PID based velocity controller as in figure 7. The system parameters and specifications of the simulated DC motor setup is listed in table II.

TABLE II: Specifications of simulated DC motor and the controller

Specifications	Values
k_t	$0.135[Nm/A]$
J	$0.000072[Nms^2/rad]$
B	$0.02045[Nms/rad]$
τ_{sf}	$0.0182[Nm]$
K_p	5500
dt	$200[\mu s]$

DC motor parameters were presumed to be constant throughout the simulation. The unstructured uncertainties such as environmental condition changes, hysteresis and saturation were neglected. A DoB integrated DC motor was used to generate simulation data. Armature current, angular velocity, angular acceleration, and the DoB estimation were recorded for the parameter estimation process. A random velocity reference which is presented in figure 8 , had been used to evaluate the accuracy of the proposed method.

The simulations were carried out under two scenarios with different number of unknown parameters to examine the convergence performance of the proposed method. In each simulation, NRA was performed on recorded data for 5 iterations.

In the first simulation scenario, variations of inertia ($\triangle J$) was set to zero. It was carried out only considering the static friction and coefficient of viscous friction. The modified model equation that was used in this simulation is expressed in equation (30).

$$\hat{\tau_{dis}}(k) = B\dot{\theta}(k) + \tau_{sf} \tag{30}$$

The results are shown in figures 9,10 and 11. The 3D and 2D contour spaces which are shown in figure 9 and 10 represent the objective function behaviour. These graphs reveal that the objective function has a global minima and the path that NRA underwent to reach minima. Figure 11:(a) shows the convergence of the objective function described in equation (21). Since the objective function has quickly attained a stable value, the appropriateness of the NRA for parameter estimation has been justified. Figure 11:(b) and 11:(c) represents the convergence of estimated system parameters as the number of iterations increase. Estimated values of the simulation agrees quite well with the actual values which are tabulated in table III.

In the second simulation variation of inertia ($\triangle J$) also considered. Hence,the model equation is in the form of equation (18). Figures 12:(a),(b),(c), and (d) show the convergence of loss function,static friction, estimated coefficient of viscous friction, and variation of inertia against the number of iterations. Despite the number of unknown parameters the NRA

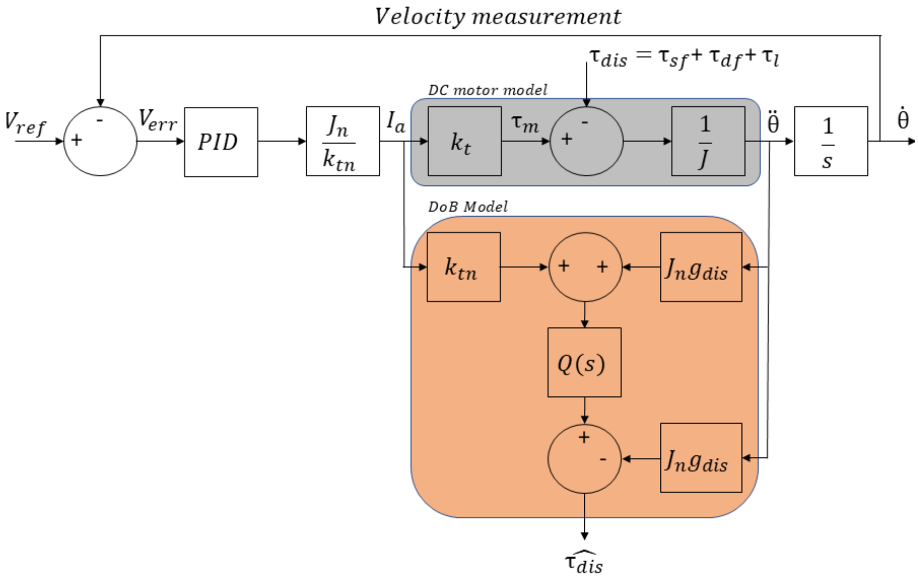


Fig. 7: Model of a DC motor integrated with a velocity controller and a DoB

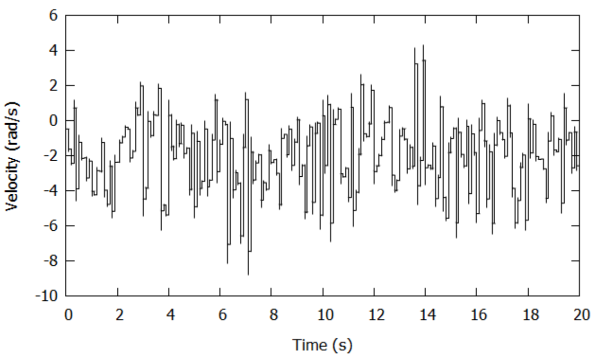


Fig. 8: Velocity reference to the controller

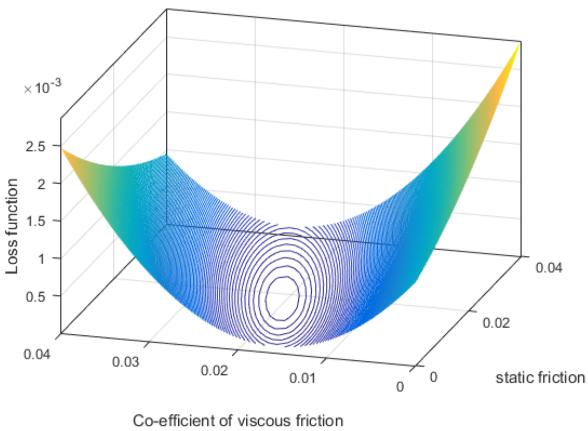


Fig. 9: 3D contour space of loss function

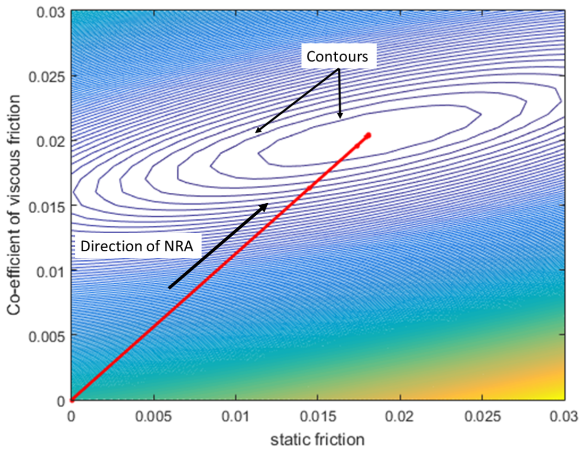
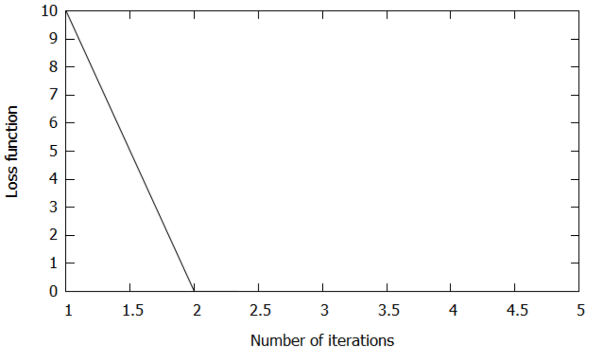


Fig. 10: Path of NRA in contour space

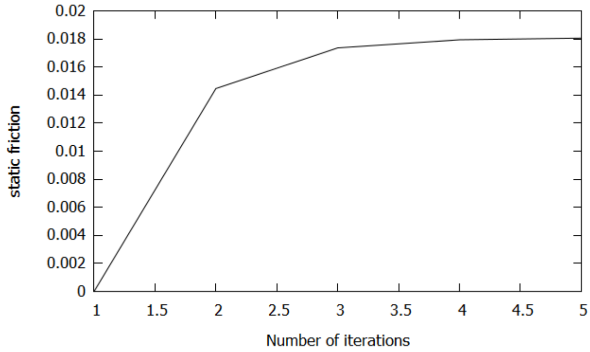
has estimated the parameters with a sound accuracy.Estimated and actual value comparison is shown in table III.

VI. Conclusion

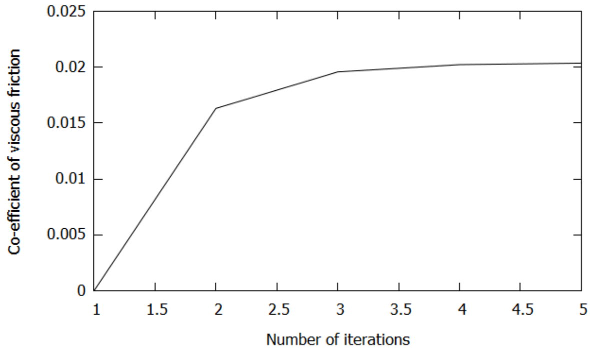
In this study, a novel iterative method of DC motor parameter estimation has been introduced. Accuracy of dc motor parameters in small scale applications is low in traditional methods of dc motor parameter estimation methods. However, accurate estimation of dc motor parameters is crucial for performance of small scale motion applications. This method is based on the disturbance observer (DOB) estimations of the dc motor. A regression model that relates system parameters and motor parameters to the DoB estimation has been derived in this study. Motor parameters can be estimated by optimizing the derived regression model. Newton Rapshson algorithm has



(a)

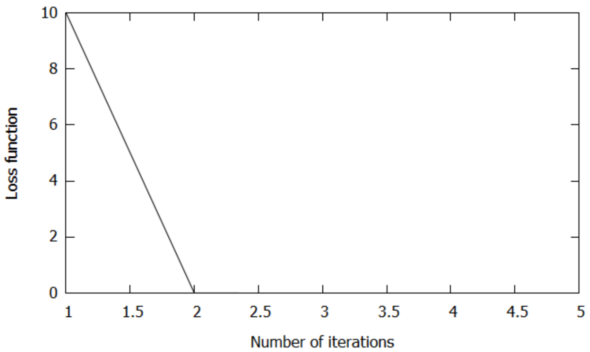


(b)

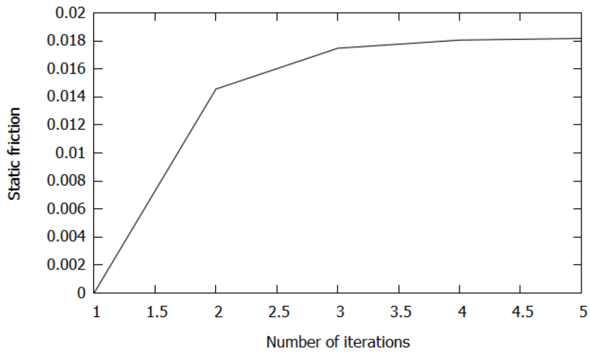


(c)

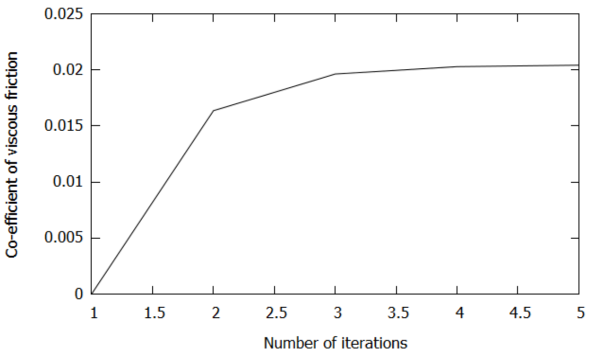
Fig. 11: Test - 2 results a) Convergence of $E(A)$ b) Convergence of τ_{sf} c) Convergence of B



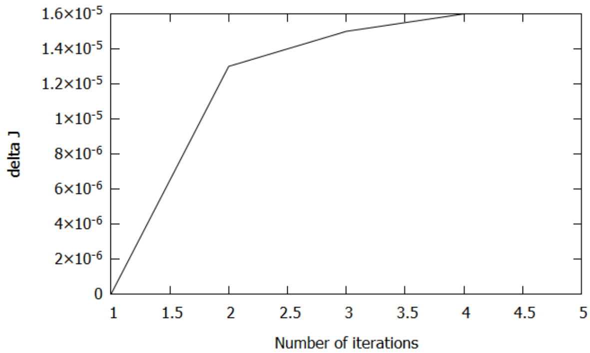
(a)



(b)



(c)



(d)

Fig. 12: Test - 2 results a) Convergence of $E(A)$ b) Convergence of τ_{sf} c) Convergence of B d) Convergence of $\triangle J$

TABLE III: Test results

Parameter	Actual Value	Estimated Value
Test - 1		
τ_{sf}	$0.0182[Nm]$	$0.0181[Nm]$
B	$0.02045[Nms/rad]$	$0.0204[Nms/rad]$
Test - 2		
τ_{sf}	$0.0182[Nm]$	$0.0181[Nm]$
B	$0.02045[Nms/rad]$	$0.0204[Nms/rad]$
$\triangle J$	$0.00002[Nms^2/rad]$	$0.0000159[Nms^2/rad]$

been selected to optimize the derived regression model over other optimization algorithms such as gradient decent due to its accuracy and speed. The validity of the proposed method were confirmed and compared in the simulations section.

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