

Adaptive Current Control Method by Online Estimation the Motor Coil's Resistance using EKF and UKF

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Abstract

This paper addresses the challenge of maintaining the current closed-loop performance of DCBL systems under conditions of significant coil temperature variations and limited bandwidth. A Kalman filter-based algorithm is proposed to estimate coil resistance in real time, enabling the adaptive tuning of a PI controller's integral gain k_I based on the estimated resistance. The algorithm is built on coupled electrical and thermal dynamics, with an augmented state-space model incorporating an additional state variable to account for unknown environmental temperature.

The resistance estimation problem is modeled using a nonlinear three-dimensional state-space framework and solved using two methods: the Extended Kalman Filter (EKF) and the Unscented Kalman Filter (UKF). Simulation results demonstrate that both methods effectively estimate the coil resistance with high accuracy and rapid convergence. However, the UKF shows a slight edge in terms of convergence time and maximum error during transient conditions.

The simulations further validate the performance improvement of the closed-loop system, where resistance estimation enables the controller to adapt to plant parameter variations, resulting in enhanced alignment between reference and actual current responses. The proposed approach demonstrates robustness and applicability to DCBL systems operating under dynamic and constrained conditions.

1 Introduction

DC Brushless motors (DCBL) are widely used in many applications. In most of these applications, the motor is driven by current control implemented via an internal control loop. This loop incorporates current measurement as feedback (input to the controller) and terminal voltage as control commands (output from the controller). The model of the Plant for the current control design is usually a first-order system, [1] and [2], where the coil's resistance and induction are coefficients of plant's denominator polynomial. Since the coil resistance

changes with temperature, the plant dynamics also vary when the motor is heated. In some applications, the change in the coil's resistance can exceed 50% of the resistance at room temperature. The control design needs to take these changes in coil resistance into consideration in order to maintain consistent current control performance.

In current control, a Proportional-Integral (PI) controller is typically employed. There are two primary methods for tuning the parameters of the PI controller parameters:

- Assuming one can set the crossover frequency of the open loop significantly higher than one over the Plant's time constant (or the Plant's pole), by treating the plant as a pure integrator, one can set the PI zero and gain according to the specified stability margin and crossover frequency.
- Cancel the plant pole with the PI zero and set the PI gain so that the open-loop gain will be equal the crossover frequency.

While the first method deals with changes in the plant parameters inherently, it cannot be applied in cases where it is impossible to set the crossover frequency significantly higher than one over the time constant. This occurs either when the coil's time constant is low and/or when the loop sample rate is low. The second method can't be applied when the coil resistance changes.

In [3], a method for Online Parameter Estimation and Adaptive Control of an Interior Permanent Magnet Synchronous Motor (IPMSM) is introduced. The Affine Projection Algorithm is proposed, focusing on parameter estimation only (not state estimation). Therefore, the influence of coil current on resistance is not taken into account.

In this paper a method to control the current under conditions of significant resistance changes and low time constants and/or low sample rates is proposed. The concept is to utilize the second method and implement Kalman-filter-based algorithms for an online estimation of the coil resistance, considering that the motor pole is a function of the coil resistance.

In the next section, a Linear Time-Invariant (LTI) current dynamics model is introduced. A justification for using a first-order model for the plant is provided, and classical methods for tuning the current controller are reviewed. In section 3 a non-LTI model of the current control plant is developed. This development is used in Section 4 to formulate the nonlinear state-space model required for the Kalman filter-based algorithm implementation. The Extended Kalman Filter (EKF) and the Unscented Kalman Filter (UKF) are then formulated in Sections 5 and 6 respectively. A simulation built to test the performance of the estimation algorithms is described in Section 7. The paper concludes with a summary.

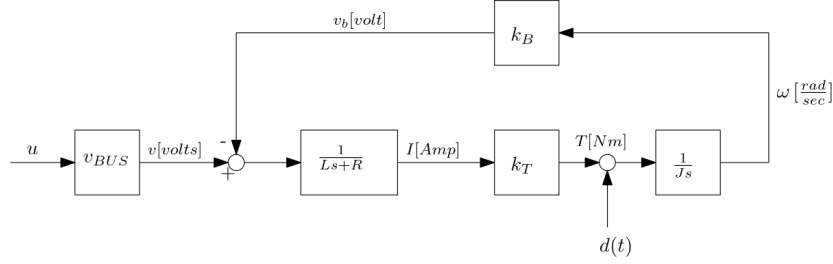


Figure 1: Full current plant block diagram

2 LTI current dynamics Modeling and conventional control design methods

In a DCBL motor, the current controller sets the average voltage at the coil terminals by adjusting the duty cycle of a high frequency square wave signal (Pulse Width Modulation, or PWM) that switches the inverter's H-bridge transistors. As a result, a current begins to develop in the motor's phase according to Kirchhoff's laws (with a resistor and coil in series). This current generates torque, causing the motor's axis to accelerate; the acceleration level is equal to the ratio of the torque to the rotational inertia. As a result, an angular velocity starts to develop and back EMF voltage is generated. This back EMF voltage is subtracted from the control voltage.

A block diagram of the full dynamics of current control plant is presented in figure 1, where u is the controller command in bus voltage ratio, I in the current in *Ampere*s, R is the phase to phase resistance in Ω , L is the phase to phase inductance in *Henry*, k_T is the motor torque constant in $\frac{Nm}{Ampere}$, k_B is the motor back EMF constant in $\frac{volts}{rad/sec}$, v_{BUS} is the bus voltage in voltage and J is the combined inertia of the motor and load in $Kg \cdot m^2$. The disturbance, $d(t)$, encompasses all non-modeled dynamics between torque and angular velocity, such as friction, external torque, and higher-order dynamics. By analyzing the block diagram, the transfer function between the control command u and measured current is extracted,

$$P(s) = \frac{v_{BUS} J s}{J L s^2 + J R s + k_T \cdot k_B} \quad (1)$$

Rearrange equation (1) as follows:

$$P(s) = \frac{\frac{v_{BUS} J}{k_T \cdot k_B} s}{\frac{J L}{k_T \cdot k_B} s^2 + \frac{J R}{k_T \cdot k_B} s + 1} \quad (2)$$

Equation (2) is a second-order transfer function that can generally have either two real poles or two adjacent complex poles, depending on the values of the coefficients in the Laplace polynomial of the denominator. In the case of a

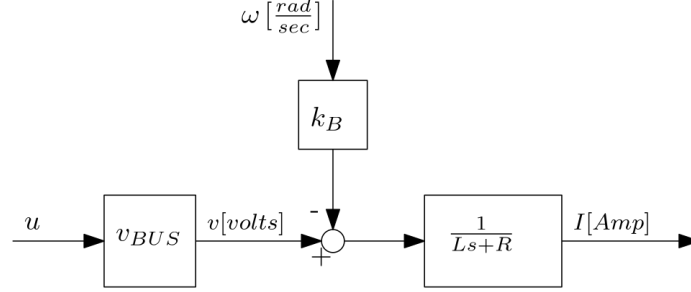


Figure 2: Simple current plant block diagram

brushless motor, the phase resistance R is three orders of magnitude higher than the phase inductance L , so the denominator of equation (2) can be approximated by the product of two first-order polynomials as follows:

$$P(s) = \frac{\frac{v_{BUS}J}{k_T \cdot k_B} s}{(\tau_E s + 1)(\tau_M s + 1)} \quad (3)$$

where τ_E and τ_M are the electrical and the mechanical time constants respectively. Their values are calculated by comparing the denominator of the plants in equations (2) and (3) and using the assumption that $\tau_M \gg \tau_E$:

$$\tau_M = \frac{JR}{k_T \cdot k_B} \quad (4a)$$

$$\tau_E = \frac{L}{R} \quad (4b)$$

Let ω_B denote the crossover frequency of the open loop of the current loop design. The following relations typically hold: $\frac{1}{\tau_M} \ll \frac{1}{\tau_E} \ll \omega_b$. This relationship, together with the fact that the current controller contains an integrator, causes the open loop gain at the frequency of $\frac{1}{\tau_M}$ to be very high, which makes the low-frequency dynamics of the plant have little influence on loop stability and performance, and the pole related to the mechanical time constant can be canceled with the plant zero in the origin. The approximated transfer function of the plant will be simply:

$$P(s) = \frac{v_{BUS}}{Ls + R} \quad (5)$$

and the block diagram is according to figure 2.

As mentioned previously, the controller is of PI type, and its transfer function can be parameterized as follows:

$$C(s) = k_P \left(1 + \frac{k_I}{s} \right) \quad (6)$$

with k_P is the controller gain and $-k_I$ is the controller zero. There are two principle strategies to tune the parameter of the controller.

2.1 First control design method

Assuming we can design a controller such that the open-loop crossover frequency significantly exceeds the plant pole value ($\omega_c \gg R/L$), it is appropriate to approximate the plant described by equation (5) as a pure integrator.

$$\tilde{P}(s) \approx \frac{1}{Ls} \quad (7)$$

The open loop transfer function will be:

$$\tilde{Q}(s) = \frac{\frac{k_P k_I}{L} v_{BUS} (s/k_I + 1)}{s^2} \quad (8)$$

By choosing the value of controller as follows:

$$\begin{aligned} k_I &= r\omega_c \\ k_P &= \frac{\omega_c L}{r \cdot v_{BUS} \sqrt{1/r^2 + 1}} \end{aligned} \quad (9)$$

the open loop cross-over frequency will be ω_c , and r ($0 < r < 1$) is the zero to crossover ratio and its value is set according to the required phase margin. Smaller r higher phase margin and vice versa. This method decrease the sensitivity of the closed loop performance to change in the plant parameters.

To illustrate the first design method, let's consider the following motor and design parameters: $R = 6.3 \text{ Ohm}$, $L = 3 \text{ mH}$, $\omega_c = 1,500 \cdot 2\pi \text{ rad/sec}$, and $r = 0.5$. Utilize equation (9) to compute the controller coefficients, then substitute these coefficients and the parameters into equations (6) and (5). Employ the obtained controller and plant transfer functions to determine the open-loop ($Q(s) = C(s) \cdot P(s)$) and closed-loop ($G(s) = \frac{Q(s)}{1+Q(s)}$) transfer functions. Figures 3, and 4 illustrate the open and closed-loop frequency response Bode plots for both, the nominal case and the scenario where the resistance is 60% higher, yet with controller parameters calculated using the nominal resistance value.

As can be seen from the figures big change in the resistance make small change in the closed loop dynamics!

2.2 Second control design method

In this method the plant was modeled as in equation (5) and the controller as in equation (6). The controller parameter are set as follows:

$$\begin{aligned} k_I &= \frac{R}{L} \\ k_P &= \frac{\omega_c L}{v_{BUS}} \end{aligned} \quad (10)$$

Substitute the above value into equation (6) and calculate the open loop transfer function and the closed loop transfer function, as it was performed in the 1st

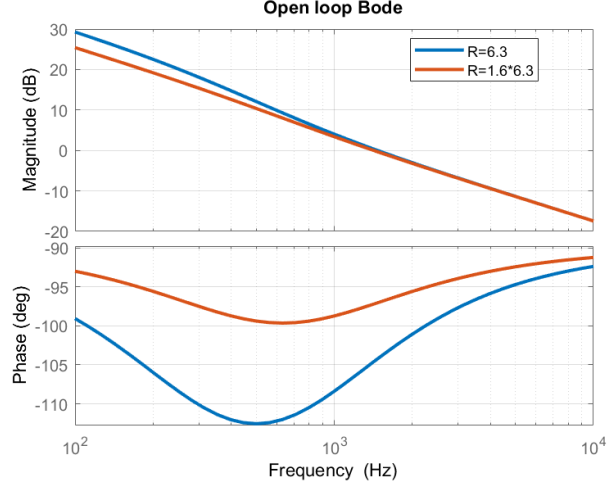


Figure 3: Open loop frequency response Bode, $P(s)$ taken from (5) with two resistance (R) values, the nominal value & 60% higher than the nominal, & $C(s)$ taken from (6) and the parameter was set according of the design example of the 1st method

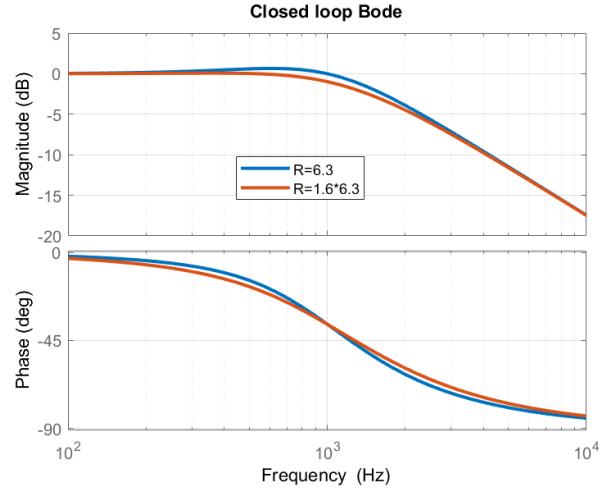


Figure 4: Closed loop frequency response Bode diagram ($G(\omega j)$, where $G(s) = \frac{Q(s)}{1+Q(s)}$) of the example of the 1st design method

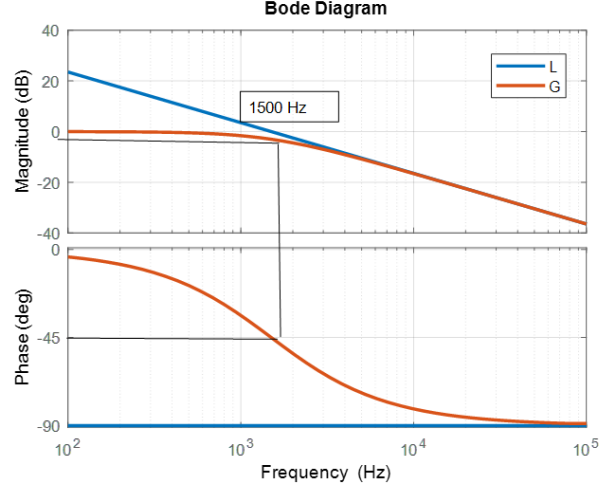


Figure 5: Example of open (blue) and closed (red) loops Bode diagrams of the 2nd design method

method in section 2.1, yields:

$$\begin{aligned} Q(s) &= \frac{\omega_c}{s} \\ G(s) &= \frac{\omega_c}{s + \omega_c} \end{aligned} \quad (11)$$

Figures 5 presents the open and the closed loop Bode, and figure 6 presents the open loop Nichols. As can be seen from the figures, in this design method the resulted closed loop transfer function as the following characteristics:

- Crossover frequency equal to the loop bandwidth (-3 dB & -45 degree).
- Infinite Gain margin.
- 90-degree Phase margin.

Using this method for the case where the resistance of the plant is 60% higher than the nominal value yields the following open-loop transfer function:

$$Q(s) = \frac{\omega_c(Ls + R)}{s(Ls + 1.6R)} \quad (12)$$

Figure 7 presents the open-loop and closed-loop frequency responses for the case of 60% higher resistance.

To illustrate the influence of the higher resistance on the loop performance, figure 4 presents steps responses of the current loop. The controller designed by the second-method (with the nominal resistance), and the plants are the

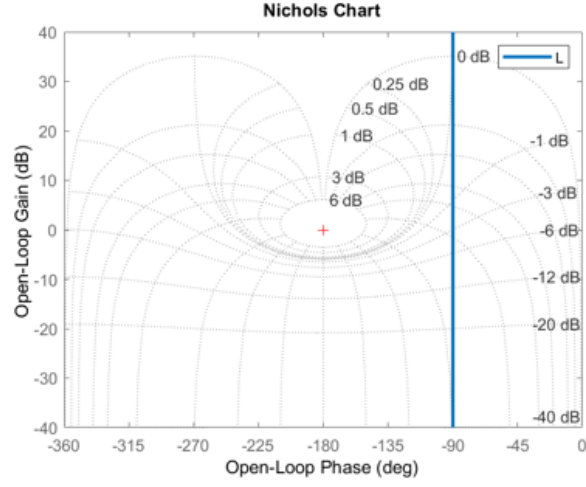


Figure 6: Example of open loop Nichols chart of the second design method

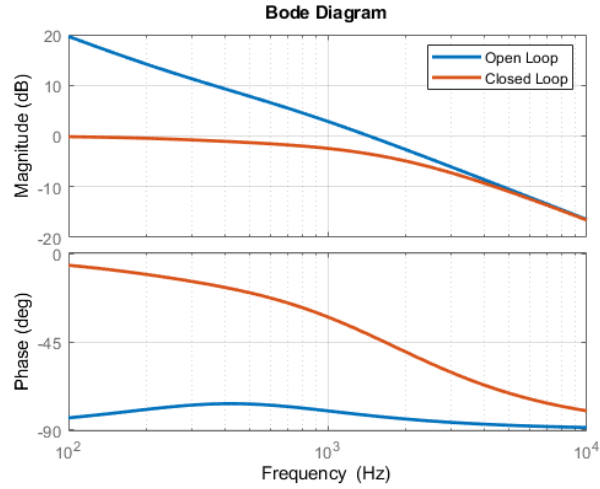


Figure 7: Example of open (blue) and closed (red) loops Bode diagrams of the 2^{nd} design method s for the case of 60% higher resistance

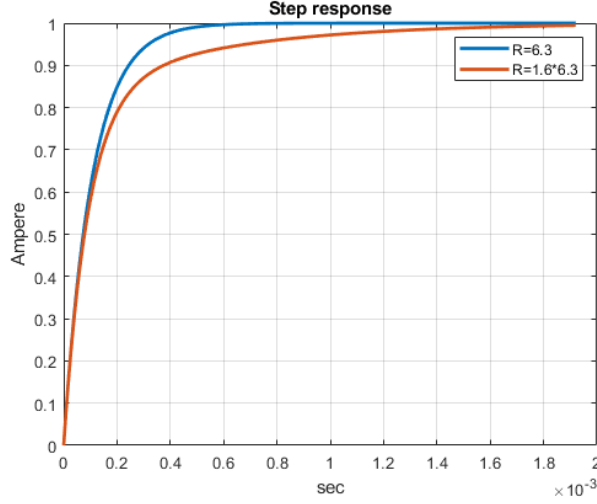


Figure 8: Comparison of closed-loop step responses. The controller is designed according to the second design method, and the plants are the nominal one and the one with 60% higher resistance

nominal one and the one with 60% higher resistance. As seen in the graph of figure 8, the response with 60% higher resistance is much slower than that with the nominal resistance. For example, the time it takes to reach a current of 0.99 Amperes is 1.6 ms with 60% higher resistance, while with the nominal resistance it is less than 0.5 ms.

2.3 Design methods summary

The following points summarized the conventional design method presented in previous sections:

- The first design method is simpler & deal with resistance change inherently
- Since this method requires the crossover frequency to be significantly higher than the plant's pole, it cannot be applied in cases where either the pole frequency is high (indicating a low coil time constant) or the crossover frequency is limited (due to a low sample rate, for example).
- The closed loop performance of the pole/zero cancellation method (method 2) is sensitive to the accuracy of the knowledge of the resistance value.
- To incorporate online estimation of the coil resistance, an Kalman Filter (KF) based algorithm is proposed.
- The KF based algorithm utilizes the voltage/current dynamics and the measured current to estimate the resistance value.

3 Non LTI Current Dynamics Modeling

To estimate the coil resistance, the dynamics of the current and the resistance need to be formulated in state space. The differential equation that describe the voltage-current relationship is derived from equation (5) and block diagram of figure 2 as follows,

$$\dot{I}L + I \cdot R = v_{BUS} \cdot u - k_B \cdot \omega \quad (13)$$

where all the parameters are defined in section 2.

To drive the current differential equation let us assume that the resistance of the coil is proportional to the coil temperature.

$$R = R_0 + \alpha(T - T_0) \quad (14)$$

Where R is the resistance at temperature T in K , R_0 is the resistance at the room temperature T_0 and α the temperature to resistance coefficient in $\frac{\Omega}{K}$.

The dynamics of the temperature follow the power balance principle, where the difference between the input power and the output power is equal to the temperature rate multiplied by the heat capacitance:

$$\dot{T} \cdot C_T = q_{in} - q_{out} \quad (15)$$

Here, T represents the coil temperature in K , C_T is the thermal capacitance in J/K , and q_{in} and q_{out} are the input and output power in $Watts$ respectively. Considering that the input power is approximately equal to the electrical power input to the coil ($q_{in} = I^2/R$), and it's common to assume that the output power is proportional to the temperature difference between the coil and the environment ($q_{out} = \gamma(T - T_E)$), where γ is the heat desptive coefficient in $\frac{Watts}{K}$ and T_E is the environment temperature in K , we have:

$$\dot{T} \cdot C_T = I^2 R - \gamma(T - T_E) \quad (16)$$

Rearranging equation (16), we get:

$$\tau \dot{T} = -T + \frac{I^2 R}{\gamma} + T_E \quad (17)$$

Where $\tau = C_T/\gamma$ is the thermal time constant in sec . Expressing T from equation (14) and substituting it into equation (17), we obtain:

$$\tau \dot{R} = -R + \frac{\alpha}{\gamma} I^2 R + \alpha T_E \quad (18)$$

Define $\beta = \alpha/\gamma$ and $R_E = \alpha T_E$,

$$\tau \dot{R} = -R + \beta I^2 R + R_E \quad (19)$$

Equation (19) describes the final resistance dynamics model. The model comprises three parameters: τ , β and R_E . In the subsequent sections, it is assumed that the first two parameters are known constants. As will be elaborated, the 3rd parameter, R_E will be regarded as an unknown constant, and its value will be estimated as part of the KF framework.

4 State-space formulation of Current-Resistance Dynamics

Equations (13) and (19) describe the dynamics of the current and resistance. To utilize these dynamics for the estimation of resistance, these equations need to be formulated in state-space and include process and measurement noise.

There are two natural states, the current and the resistance. However, to address the unknown environmental temperature, the 'environmental resistance' R_E is augmented. Since the dynamics of the environmental temperature are unknown, it will be treated as an unknown parameter, i.e., its derivative has zero deterministic part.

The augmented state vector is:

$$\mathbf{x} = \begin{pmatrix} I \\ R \\ R_E \end{pmatrix} \quad (20)$$

The input for the state space model are the terminal voltage command and angular velocity,

$$\mathbf{u} = \begin{pmatrix} u \\ \omega \end{pmatrix} \quad (21)$$

Given the definitions of equations (20) and (21), the state-space formulation is

$$\begin{aligned} \dot{\mathbf{x}} &= \mathbf{f}(\mathbf{x}, \mathbf{u}) + \mathbf{w} = \begin{pmatrix} -\frac{x_2 x_1}{L} + \frac{v_{BUS}}{L} u_1 - \frac{k_{BEMF}}{L} u_2 \\ \frac{-x_2}{\tau} + \frac{\beta x_2^2 x_1}{\tau} + \frac{x_3}{\tau} \\ 0 \end{pmatrix} + \mathbf{w} \\ y &= h\mathbf{x} + \nu = \begin{pmatrix} 1 & 0 & 0 \end{pmatrix} \mathbf{x} + \nu \end{aligned} \quad (22)$$

where $\mathbf{f} \equiv (f_1 \ f_2 \ f_3)^T$ and h are implicitly defined in the equation and $\mathbf{w}$ and ν are the process and measurement noises which are both assumed to be zero mean multivariate Gaussian noises with covariance Q and R_D respectively.

The above state space equation is nonlinear continuous state space. To utilize the EKF, linearization and discretization of these equations need to be performed. As is usually performed in EKF formulation, it is assumed that the state is given at time step n . Using Taylor series, one can approximate a linear relation to calculate the state rate at the next time step $n + 1$. The change in the state rate approximately equal to a matrix of partial derivative of the nonlinear state vector function $\mathbf{f}$ with respect to the state vector $\mathbf{x}$, calculated on the current estimated state, multiplied by the difference between the next state and the current state vectors.

$$A \equiv \frac{\partial \mathbf{f}_i}{\partial \mathbf{x}_j} = \begin{pmatrix} -\frac{x_2}{L} & \frac{2\beta x_2 x_1}{L} & 0 \\ -\frac{x_1}{L} & -1/\tau + \frac{\beta x_1^2}{L} & 1/\tau \\ 0 & 0 & 0 \end{pmatrix} \quad (23)$$

An approximation of the discrete state-space matrix is obtained by utilizing the matrix A and the sample time T_s as follows:

$$F(\mathbf{x}) = e^{AT_s} \approx I + AT_s = \begin{pmatrix} 1 - \frac{x_2}{L}T_s & \frac{2\beta x_2 x_1}{L}T_s & 0 \\ -\frac{x_1}{L}T_s & 1 - T_s/\tau + \frac{\beta x_1^2}{L}T_s & T_s/\tau \\ 0 & 0 & 1 \end{pmatrix} \quad (24)$$

The discrete process covariance matrix is approximated from the continue process covariance matrix by,

$$Q_D = \frac{Q}{T_s} \quad (25)$$

5 EKF frameworks

It suitable to describe the EKF in two steps:

- Time update (Prediction): Assuming that at step n , the estimated state $\hat{\mathbf{x}}(n/n)$ and the state covariance matrix $P(n/n)$ are known, the next step time prediction of the state and the covariance are:

$$\hat{\mathbf{x}}(n/n+1) = \hat{\mathbf{x}}(n/n) + \mathbf{f}(\hat{\mathbf{x}}(n/n), \mathbf{u}(n))T_s$$

$$P(n/n+1) = F(\hat{\mathbf{x}}(n/n))P(n/n)F(\hat{\mathbf{x}}(n/n))^T + Q_D$$

- Kalman gain calculation

$$K = P(n/n+1)h^T[hP(n/n+1)h^T + R_D]^{-1}$$

- Measurement update (Correction):

$$\hat{\mathbf{x}}(n+1/n+1) = \hat{\mathbf{x}}(n/n+1) + K(\tilde{y}(n+1) - h\hat{\mathbf{x}}(n/n+1))$$

$$P(n+1/n+1) = [I - Kh]P(n/n+1)[I - Kh]^T + KR_DK^T$$

where $\tilde{y}(n+1)$ is the measured current on step $n+1$

6 Unscented Kalman Filter

The Unscented Kalman Filter (UKF) is an alternative approach to linearization. While the Extended Kalman Filter (EKF) addresses non-linearity through analytical linearization, the UKF performs statistical linearization based on a set of predefined rules. The Unscented Kalman Filter consists of the following steps [4]:

- Assuming the estimated state, $\hat{x}(n/n)$, and state covariance, $P(n/n)$, are known on time n , compute sigma points $\mathcal{X}$ as follows:

$$\mathcal{X}^{[0]} = \hat{x}(n/n)$$

$$\mathcal{X}^{[i]} = \hat{x}(n/n) + \left(\sqrt{(N+\lambda)P(n/n)} \right)_i, i = 1, \dots, N$$

$$\mathcal{X}^{[i]} = \hat{x}(n/n) - \left(\sqrt{(N+\lambda)P(n/n)} \right)_i, i = n+1, \dots, 2N$$

where λ is scaling factor, N is the state dimension and the expression $\left(\sqrt{(N+\lambda)P(n/n)} \right)_i$ refer to the i -th column of the square root of the matrix $(N+\lambda)P(n/n)$. The matrix square root is defined such that if we have a matrix S satisfying the following condition: $SS^T = P$, then S is the square root of the matrix P .

- Computing the weights of Sigma Points:

$$\omega^{[0]} = \frac{\lambda}{N+\lambda}$$

$$\omega^{[i]} = \frac{1}{2(N+\lambda)}, i = 1, \dots, 2N$$

- Time update (prediction): compute the mean and the covariance of the time updates state:

$$\hat{x}(n/n+1) = \sum_{i=0}^{2N} \omega^{[i]} \mathbf{g}(\mathcal{X}^{[i]}, u)$$

$$P(n/n+1) =$$

$$\sum_{i=0}^{2N} \omega^{[i]} \left(\mathbf{g}(\mathcal{X}^{[i]}, u) - \hat{x}(n/n+1) \right) \left(\mathbf{g}(\mathcal{X}^{[i]}, u) - \hat{x}(n/n+1) \right)^T + Q_D$$

where $\mathbf{g}(\mathcal{X}^{[i]}, \mathbf{u}) = \mathcal{X}^{[i]} + \mathbf{f}(\mathcal{X}^{[i]}, u)T_s$, and $\mathbf{f}$ is define in equation (22).

- Predicted measurement and predicted measurement covariance computation:

$$\mathcal{Y} = h\mathcal{X}$$

$$\hat{y} = \sum_{i=0}^{2N} \omega^{[i]} \mathcal{Y}^{[i]}$$

$$P_{yy} = \sum_{i=0}^{2N} \omega^{[i]} \left(\mathcal{Y}^{[i]} - \hat{y} \right) \left(\mathcal{Y}^{[i]} - \hat{y} \right)^T + R_D$$

- Cross correlation and Kalman matrix computation:

$$P_{xy} = \sum_{i=0}^{2N} \omega^{[i]} \left(\mathcal{X}^{[i]} - \hat{x}(n/n+1) \right) \left(\mathcal{Y}^{[i]} - \hat{y} \right)^T$$

$$K = P_{xy} P_{yy}^{-1}$$

- Measurement updated (correction)

$$\hat{x}(n+1/n+1) = \hat{x}(n/n+1) + K [\tilde{y}(n+1) - \hat{y}]$$

$$P(n+1/n+1) = P(n/n+1) - K P_{yy} K^T$$

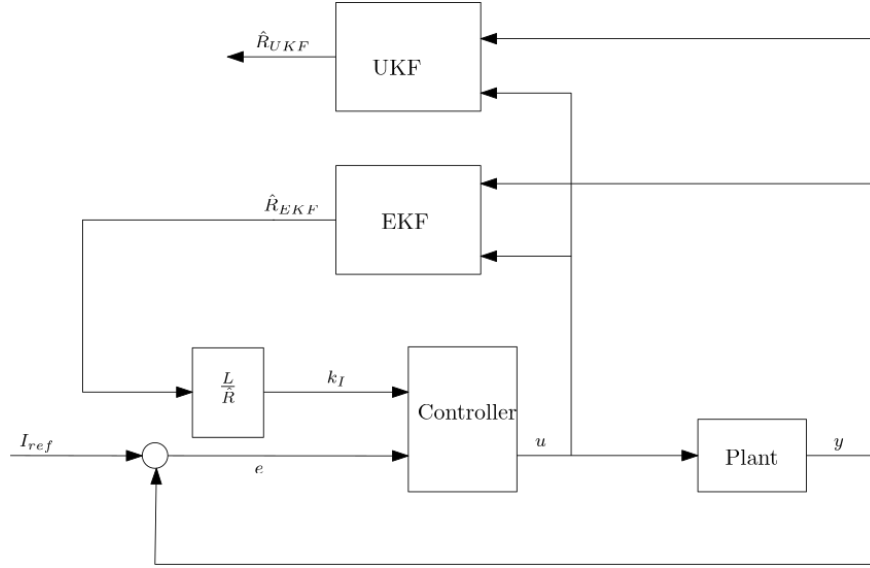


Figure 9: Innovative current control block diagram

7 Simulation

To test the algorithms, a simulation was constructed. Figure 9 presents the block diagram of the simulation. The simulation uses the resistance-current dynamics of equations (13) and (19) that developed at section 3. These equations define the relation between the input control command and motor velocity to the real current and resistance. For simplification we assumed that the angular velocity is zero and there is no back EMF effect. This relation designated as a Plant block in the block diagram.

The Plant's input, u , is generated by the controller, it is calculated by applying PI equation (equation (7)) on the current error. The controller coefficients, k_P and k_I , are set according to equation (10), were the value of k_I updated online using the estimated coil resistance ($k_I = \frac{L}{\hat{R}}$).

The value of $\hat{R}$ is calculated by applying EKF and UKF algorithms. as describes at sections 5 and 6 respectively. The algorithms designated in EKF and UKF blocks. The input to the blocks are the control command and the measured current.

The values of the Plant's constant parameters that was used in the simulation are detailed in Table 1, and the reference current signal in the simulation was square wave describe in figure 10

The "environmental" resistance, R_E , in the Plant equation was set to 8.6 ohm, while the initial value of environmental resistance in the EKF and UKF state was set to the room temperature resistance, i.e., R_0 .

The initial state and covariance for the EKF and UKF were set to:

Parameters	Units	Value
β	Ohm/watt	0.1
τ	sec	23
L	Henry	3e-3
R_0	Ohm	6.3
v_{BUS}	Volts	28

Table 1: Simulation parameters

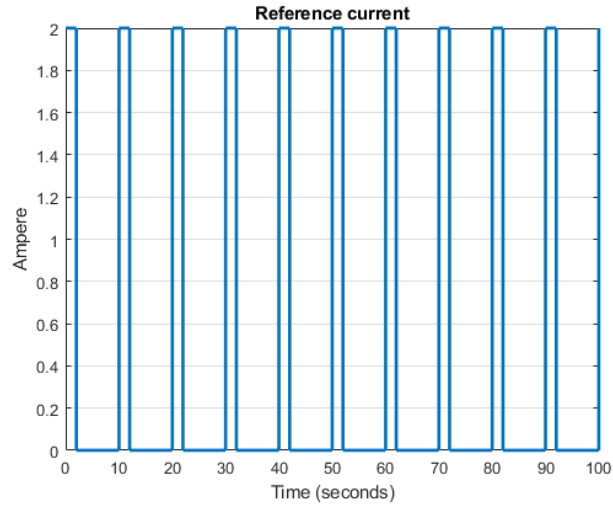


Figure 10: Simulation Reference current signal

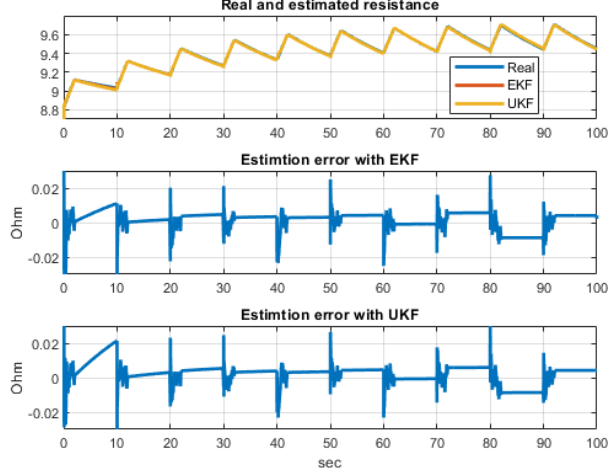


Figure 11: Simulation results: real and estimated coil resistance as function of time (upper plot). Estimation error with EKF (middle plot) and estimation error with UKF (bottom plot). The y axis of the error plots scaled to about ± 0.03 Ohm to clarify the error nature at steady state

$$\hat{\mathbf{x}}_0 = \begin{bmatrix} 0 \\ R_0 \\ R_0 \end{bmatrix} \quad (26)$$

$$P_0 = 100 \cdot \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (27)$$

and R_0 in the resistance at room temperature, i.e., 6.3 ohm. The scale factor parameters λ , for the UKF set to $\lambda = N(\epsilon^2 - 1)$ with $\epsilon = 0.001$.

Figures 11 and 12 present the values of the coil's real and estimated resistance as a function of time, along with the estimation error for the two methods. As shown in Figure 11, the estimation error at steady state becomes very small. However, at the beginning of the simulation, as depicted in Figure 12, there is a significant difference between the real and estimated resistance. The UKF demonstrates an advantage in terms of both convergence time and maximum error during the convergence phase.

Figure 12 presents the simulation reference and actual current. Similar to Figure 11, as the simulation progresses, the difference between the reference and the actual current decreases. This is due to the fact that the controller adapts to the plant parameters.

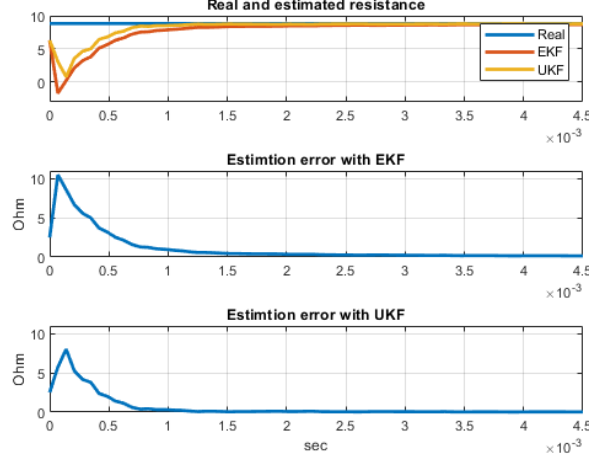


Figure 12: Simulation result (zoom in on x axis zoom out in y axis of figure 11) : real and estimated coil resistance as function of time (upper plot). Estimation error with EKF (middle plot) and estimation error with UKF (bottom plot)

Figure 13 presents the closed-loop current response. As shown in the figure, there is a significant improvement in the current response during the last step compared to the response in the first step. This improvement results from the convergence of the resistance estimation, which 'learns' the value of R_E . Consequently, this enhances the accuracy of the R , estimation, leading to better alignment of the controller's parameters with the plant's dynamics..

8 Summary

This paper addresses the challenge of maintaining the current closed-loop performance of DCBL systems under special conditions, such as significant changes in coil temperature and limited bandwidth.

The proposed solution involves applying a Kalman filter-based method to estimate the coil resistance, combined with a PI controller that adapts the coefficient k_I based on the estimated resistance. The model used for the Kalman filter algorithm is derived from coupled electrical and thermal differential equations. To account for the unknown environmental temperature, an additional state variable is introduced into the model.

As a result of this modeling approach, a nonlinear three-dimensional state-space representation is obtained, and the estimation problem is addressed using two methods: the Extended Kalman Filter (EKF) and the Unscented Kalman Filter (UKF).

Simulations illustrating the algorithm's performance demonstrate that both

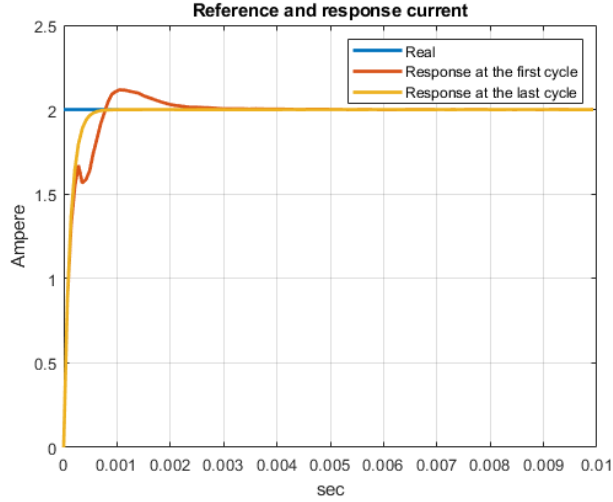


Figure 13: Reference (blue) and Closed loop current response at the first cycle (red) and at the last cycle (yellow)

methods effectively estimate the resistance quickly and accurately. However, the UKF shows slightly better performance in terms of convergence time and maximum error during the convergence phase.

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