# EFFICIENCY ESTIMATION OF THREE-PHASE INDUCTION MOTORS APPLYING DUAL EXTENDED KALMAN FILTER APPROACH WITH LEAST SQUARES INITIALIZATION

## ƯỚC LƯỢNG HIỆU SUẤT CỦA ĐỘNG CƠ ĐIỆN CẢM ỨNG BA PHA ÁP DỤNG BỘ LỌC KALMAN MỞ RỘNG KÉP VÀ KHỞI TẠO THAM SỐ BAN ĐẦU BẰNG PHƯƠNG PHÁP BÌNH PHƯƠNG TỐI THIỂU

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**ABSTRACT**

*In industrial environments, three-phase induction motors are becoming more widely used and are irreplaceable. Therefore, monitoring motor conditions, particularly efficiency, is essential to support energy optimization processes and predictive maintenance. This paper proposes a complete framework to estimate the efficiency of a 3-phase induction motor based on input voltages and output currents. A dual extended Kalman filter is used in the proposed method to estimate model states and parameters simultaneously. Additionally, the initial conditions are established by applying the least squares method to the measurement set of response currents when injecting DC voltage into the stator winding. Simulation results show that the proposed method can achieve a steady state error of less than 2% for the problem of estimating motor efficiency with a settling time of less than 0.5s.*

**Keywords:** *EKF; Induction motor; Efficiency; Non-instrusive estimation; Dual estimation.*

**TÓM TẮT**

*Trong môi trường công nghiệp, động cơ điện cảm ứng ba pha ngày càng được sử dụng rộng rãi và trở thành thiết bị không thể thay thế. Do đó, việc giám sát tình trạng động cơ, đặc biệt là hiệu suất, là điều cần thiết để hỗ trợ các quá trình tối ưu hóa năng lượng và bảo trì dự đoán. Bài báo này đề xuất một khung làm việc hoàn chỉnh để ước tính hiệu suất của động cơ cảm ứng 3 pha dựa trên điện áp đầu vào và cường độ dòng điện đầu ra. Phương pháp được đề xuất sử dụng bộ lọc Kalman mở rộng kép để ước tính đồng thời các trạng thái và tham số của mô hình. Ngoài ra, các điều kiện ban đầu được khởi tạo bằng cách áp dụng phương pháp bình phương tối thiểu cho tập dữ liệu đo của đáp ứng dòng điện khi đưa điện áp một chiều vào cuộn dây stato. Kết quả mô phỏng cho thấy phương pháp đề xuất có thể đạt được sai số xác lập nhỏ hơn 2% với thời gian xác lập nhỏ hơn 0,5s đối với bài toán ước lượng hiệu suất động cơ.*

**Từ khóa:** *Bộ lọc Kalman mở rộng; Động cơ điện cảm ứng; Hiệu suất; Ước lượng không xâm lấn; Ước lượng kép.*

## 1. INTRODUCTION

Three-phase induction motors are widely used in various industrial applications that require continuous and reliable operation, such as pumps and compressors, conveyors, machine tools, robots, and generators, etc. They occupy a large number in the factory and ensure that automation lines operate synchronously and continuously. Therefore, monitoring the efficiency of electric motors can support post-processing processes to bring benefits in optimizing energy operation and equipment maintenance (especially predictive maintenance) [1, 2]. Measuring the efficiency of electric motors during operation is still a challenge because it requires expensive measuring equipment and intrusive measurements. In addition, electric motors' performance can fluctuate over time due to aging, wear, operating conditions, and faults. Therefore, a non-intrusive and reliable approach is necessary to estimate the performance of 3-phase induction motors and track their health status.

Different methods of calculating efficiency have been mentioned in some standards for electric motors [3-5]. These methods are based on test procedures and specify techniques for obtaining specific losses depending on whether performance is determined directly or indirectly. Direct measurement involves measuring the input power based on the voltage and current supplied and the output power based on the rotational speed and torque. Indirect measurement involves measuring the input power and calculating the output power based on the losses within the motor. Many indirect measurement methods are proposed to provide alternatives in situations where direct measurement is not feasible (such as the power of the test motor is too large, machine-bearing construction is not permitted, and tests under load are not made) but still ensure precision and repeatability. However, most methods require intrusive measurement forms (voltage, resistance, mechanical power) and measurement at specific load points (no load, rated load) to determine specific losses. Therefore, it is challenging for these methods to be applied in industrial systems that require continuous operation. Numerous research efforts have been carried out to reduce the intrusive testing procedures from the above standards. For instance, El-Ibiary [6] describes a low-cost and accurate method for determining motor efficiency by applying fewer measurements on two load points, motor efficiency can be calculated from the governing equation of motor behavior as a function of input voltage, input current, motor parameters, and slip. Al-Badri et al. [7] present a novel technique for estimating refurbished induction motors' full-load and partial-load improvements from no-load tests based on the modification of the IEEE Std 112: 2004 Method 3 on data obtained from a DC test. Testing at one or two load points is necessary for the methods mentioned above. The in-service motor's temporary isolation from the production line and configuration under proper load conditions to estimate efficiency is still considered highly intrusive.

In a survey on efficiency estimation methods for in-service induction motors, Lu et al. [8] describe more than 20 of the most commonly used methods, particularly considering the motor condition monitoring requirements. Furthermore, four efficiency estimation methods have been suggested for non-intrusive in-service motor efficiency estimation and condition monitoring applications, namely ORMEL96, REMW, OHME, and especially the air-gap torque method. The air-gap torque (AGT)-based methods have been promised as the least intrusive level due to rotor speed, ☞

and stator resistance is extracted from motor input currents instead of being measured [9]. However, the stator resistance, which is required to estimate the output torque, is estimated by signal injection-based methods. This method required some extra hardware and the installation of the injection circuit in the motor control center for the mains-fed machine. Also, the injected DC signal unbalances the stator voltages and current and causes additional low power dissipation and torque distortion [9, 10]. To overcome this problem, Salomon et al. [10] propose an air-gap torque-based method using a new concept of stator resistance that includes the mechanical losses effect. This new stator resistance is estimated through a particle swarm optimization approach based on the stator flux equations and minimization of torque error at the rated operation point. Then, the obtained stator resistance is used in the AGT equations to estimate the shaft torque and efficiency. Thus, the proposed efficiency estimation method relies only on line currents, line voltages, and nameplate data, which are appropriate for in-service applications. Dlamini et al. [11] proposed a non-intrusive method for estimating motor speed using vibration signature analysis. This approach uses the compensated slip method, where the motor speed is accurately estimated using signature analysis of vibration data collected from the motor housing. The estimated motor speed is then used to calculate the performance. However, the vibration signal is susceptible because it is easily affected by other machines operating simultaneously. Furthermore, installing a vibration sensor on the motor housing is inappropriate for some applications with an embedded motor in the machine. Li et al. [12] proposed a new concept called load ratio for estimating motor efficiency under variable speed. The load ratio is the percent of actual and maximum output power used to correct the results of the estimated motor efficiency under various load conditions. Experimental results from the published database demonstrate that the proposed method can achieve a relative error of ±10% when the speed ratio is above 0.5. Promising other methods could consider the load and speed ratio in estimating motor efficiency with VFD-driven.

The primary way to estimate efficiency in 3-phase induction motors is through the equivalent circuit-based approach. The term equivalent circuit refers to a simplified representation of voltages and currents in a 3-phase motor with respect to its resistances, reactances, and slip. It can accurately determine the stray load losses used in calculating motor efficiency according to IEEE-112 Std in case all circuit parameters are known. In order to reduce the intrusive level, numerous optimization techniques were used to estimate the parameters of the equivalent circuit with the objective function constructed based on the measured voltage and current data from the terminal box [13-24]. These optimization techniques mainly belong to the category of the evolutionary algorithm, such as Genetic Algorithm (GA) or GA-based [14-19], Bacterial Foraging Algorithm [20-22], Strength Pareto Evolutionary Algorithm-based [16], and Differential Evolution [23]. However, the estimated parameters are not directly in the objective function, thus leading to the case that the objective function was optimized, but the estimated parameter is a different set (local optimum solution). Furthermore, evolutionary algorithms are very computationally expensive for determining the exact parameters of an equivalent circuit. Thus, these algorithms need to be more appropriate for on-site implementation of compact devices.

In a general analysis, the primary research problem related to efficiency estimation for 3-phase induction motors is reducing the intrusive level when installing sensor systems on the motor [6-7, 9-23]. Methods based on air-gap torque and evolutionary algorithms have further advantages because output power can be estimated based only on the signal measured from current and voltage in the terminal box. Moreover, some of the above studies concentrate on solving other problems related to efficiency estimation for refurbished motors [7, 13], under variable speed operation or VFD driven [12, 15], under unbalanced or distorted voltage [13, 14, 17, 19, 22], and under over/under-voltage [17]. However, no studies focus on estimating motor efficiency with a specific concern of building a health index for industrial predictive maintenance applications where multiple working conditions can affect motor performance. The computational cost is also a big concern for hardware limitations and on-site estimation due to the large number of motors in industrial applications.

In this paper, we propose a complete framework to estimate the efficiency of 3-phase induction motors, specifically concerning the construction of a health index for industrial predictive maintenance applications. Current and voltage measurements at the electrical terminal box are required by the proposed framework. The proposed method is based on the Dual Extended Kalman Filter for estimation of states and parameters, with the initial condition given by the least squares method.

The simulation results show that the Kalman Filter's characteristic and proposed initialization method can estimate the motor efficiency with acceptable accuracy and settling time.

The remains of this paper is organized as follows. Section 2 introduces the preliminary analysis and proposed approach. The simulation results and discussion are described in Section 3. Finally, the conclusion and feature work are provided in Section 4.

## 2. PROPOSED FRAMEWORK

This paper proposes a complete framework to estimate the efficiency of 3-phase induction motors using only the measurement signals in the electrical box. As shown in Figure 1, our framework is divided into two main stages: offline parameters initialization and online parameters and state estimation. In the offline stage, we apply a DC voltage to the stator windings to estimate the model parameters. The initial value is approximated using the least squares method to the measurement sets of phase input voltages and output currents. As a result, the proposed parameter estimation framework can achieve greater accuracy and a faster convergence time. The DC voltage is selected to be small enough not to affect components wired directly to the motor windings.

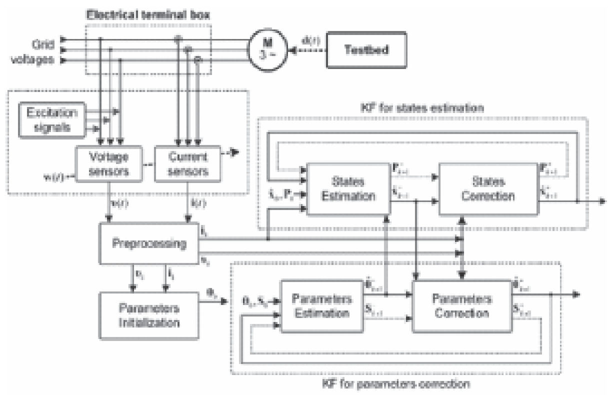


*Figure 1. The overall framework of states and parameters estimation process.*

In the online stage, we use a combination of two Extended Kalman Filter sets executing in parallel to estimate the state of the dynamic model and its parameters from the measurement signals. This approach can be effectively applied to systems where state and model parameters are unavailable or difficult to obtain [24, 25]. Finally, motor efficiency can be calculated by combining the measured instantaneous input power and estimated output power.

### 2.1. The mathematical model of an induction motor

In this study, the dynamics of a 3-phase induction motor are referenced from [26], which can be described by the following non-linear equations:

$$\begin{aligned}
\frac{di_{sd}}{dt} &= -\left(\frac{R_s}{L_\sigma}+\frac{R_r L_m^2}{L_r^2 L_\sigma}\right)i_{sd}+\frac{R_r L_m}{L_r^2 L_\sigma}\psi_{rd}+\frac{L_m}{L_r L_\sigma}p_p\omega_m\psi_{rq}+\frac{1}{L_\sigma}v_{sd}\\
\frac{di_{sq}}{dt} &= -\left(\frac{R_s}{L_\sigma}+\frac{R_r L_m^2}{L_r^2 L_\sigma}\right)i_{sd}+\frac{R_r L_m}{L_r^2 L_\sigma}\psi_{rq}-\frac{L_m}{L_r L_\sigma}p_p\omega_m\psi_{rd}+\frac{1}{L_\sigma}v_{sq}\\
\frac{d\psi_{rd}}{dt} &= \frac{R_r}{L_r}L_m i_{sd}-\frac{R_r}{L_r}\psi_{rd}-p_p\omega_m\psi_{rq}\\
\frac{d\psi_{rq}}{dt} &= \frac{R_r}{L_r}L_m i_{sq}-\frac{R_r}{L_r}\psi_{rq}+p_p\omega_m\psi_{rd}\\
\frac{d\omega_m}{dt} &= -\frac{3}{2}\frac{p_p L_m}{J_L L_r}\psi_{rq}i_{sd}+\frac{3}{2}\frac{p_p L_m}{J_L L_r}\psi_{rd}i_{sq}-\frac{1}{J_L}\tau_L\\
\frac{d\tau_L}{dt} &= 0
\end{aligned}\tag{1}$$

The state variables include $i_{sd}$ and $i_{sq}$, which represent stator stationary axis components of stator currents. $v_{sd}$ and $v_{sq}$ are stator stationary axis components of stator voltages. $\psi_{sd}$ and $\psi_{sd}$ are stator stationary axis components of stator voltages. $\omega_m$ is the motor's angular velocity, and $\tau_L$ is the total mechanical load applied to the motor's shaft. Regarding the induction motor parameters, $L_\sigma$ is the stator transient inductance, and σ is the leakage or coupling factor between the stator and rotor. $L_s$ and $R_s$ are the stator inductance and resistance. $L_r$ and $R_r$ are the rotor inductance and resistance. $p_p$ is the number of pole pairs, and $J_L$ is the total inertia of the induction motor and load.

The implementation of EKF requires the discretization of (1) with the sampling time $t_s$, which the following general form can describe from (2-3):

$$\begin{aligned}
\mathbf{x}_{k+1} &= \mathbf{A}_k\mathbf{x}_k+\mathbf{B}\mathbf{u}_k+\mathbf{d}_k^{\mathbf{x}}\\
\mathbf{y}_k &= \mathbf{H}_k^{\mathbf{x}}\mathbf{x}_k+\mathbf{w}_k^{\mathbf{x}}
\end{aligned}\tag{2}$$

where: $\mathbf{d}_k^{\mathbf{x}}$ and $\mathbf{w}_k^{\mathbf{x}}$ denote the state noise and the measurement noise for state vector, respectively. They are independent white noise with variances $\mathbf{Q}_k^{\mathbf{x}}$ and $\mathbf{R}_k^{\mathbf{x}}$, respectively.

For the parameters estimation problem, we denote $\theta = [R_s, R_r, L_s, L_r, L_m]^T$, which contains the model parameters to be estimated. The remaining parameters from the model (3) that are not estimated include the number of pole pairs $p_p$, assumed to be known, and the total inertia $J_L$, assigned to a small fixed value. The parameter vector θ is considered as constant and only affected by the process noise. Therefore, the dynamic equation for the parameters estimation problem has the form of:

$$\begin{aligned}
\boldsymbol{\theta}_{k+1} &= \boldsymbol{\theta}_k+\mathbf{d}_k^{\boldsymbol{\theta}}\\
\mathbf{y}_k &= \mathbf{H}_k^{\boldsymbol{\theta}}\mathbf{x}_k+\mathbf{w}_k^{\boldsymbol{\theta}}
\end{aligned}\tag{4}$$

Where: $\mathbf{d}_k^{\boldsymbol{\theta}}$ and $\mathbf{w}_k^{\boldsymbol{\theta}}$ denote the process noise and the measurement noise for vector θ, respectively. They are also considered independent white noise with variances $\mathbf{Q}_k^{\boldsymbol{\theta}}$ and $\mathbf{R}_k^{\boldsymbol{\theta}}$, respectively.

### 2.2. Online joint estimation of the state and parameters of an induction motor

Figure 1 illustrates the simultaneous running of two Extended Kalman Filters to jointly estimate motor state and parameters in the online stage. At each step, the two EKF units will exchange information back and forth to perform a time update of parameters and status.

Finally, both filters will perform measurement-update based on the error between the estimated state and the measured signal from the sensor. The calculation process of dual EKF can be formulated using the following sequential equations.

The time update for the motor parameters and the estimated parameters error variance are:

$$\begin{aligned}\hat{\boldsymbol{\theta}}_{k+1}^{-} &= \hat{\boldsymbol{\theta}}_{k}^{+} \\ \mathbf{P}_{\theta|k+1}^{-} &= \mathbf{P}_{\theta|k}^{+} + \mathbf{Q}_{k}^{\theta}\end{aligned} \tag{5}$$

Where $\hat{\boldsymbol{\theta}}_{k+1}^{-}$ is the time-update of the motor parameters θ at time k. $\mathbf{P}_{\theta|k}^{+}$ is the posterior estimate of the estimated parameters error variance at time k.

Similarly, the time-update for the state vector and the estimated state vector error variance are:

$$\begin{aligned}\hat{\mathbf{x}}_{k+1}^{-} &= \mathbf{A}\left(\hat{\mathbf{x}}_{k}^{+}, \hat{\boldsymbol{\theta}}_{k+1}^{-}\right)\hat{\mathbf{x}}_{k}^{+} + \mathbf{B}\left(\hat{\boldsymbol{\theta}}_{k}\right)\mathbf{u}_{k} \\ \mathbf{P}_{x|k+1}^{-} &= \mathbf{F}\left(\hat{\mathbf{x}}_{k}^{+}, \hat{\boldsymbol{\theta}}_{k+1}^{-}\right)\mathbf{P}_{\theta|k}^{+}\left(\mathbf{F}\left(\hat{\mathbf{x}}_{k}^{+}, \hat{\boldsymbol{\theta}}_{k+1}^{-}\right)\right)^{T} + \mathbf{Q}_{k}^{x}\end{aligned} \tag{6}$$

Where $\hat{\mathbf{x}}_{k+1}^{-}$ is the time-update of the state vector x at time k. $\mathbf{P}_{x|k}^{+}$ is the posterior estimate of the estimated state error variance at time k. $F_k$ is the linearization of the nonlinear function $\mathbf{f}(\mathbf{x}, \hat{\boldsymbol{\theta}}_{k+1}^{-}, \mathbf{u}_{k})$, and is constructed by equations (7).

Next, the state vector is updated by measurement information:

$$\begin{aligned}\mathbf{K}_{k}^{x} &= \mathbf{P}_{x|k+1}^{-}\left(\mathbf{H}_{k}^{x}\right)^{T}\left(\mathbf{H}_{k}^{x}\mathbf{P}_{x|k+1}^{-}\left(\mathbf{H}_{k}^{x}\right)^{T} + \mathbf{R}_{k}^{x}\right) \\ \hat{\mathbf{x}}_{k+1}^{+} &= \hat{\mathbf{x}}_{k+1}^{-} + \mathbf{K}_{k}^{x}\left(\mathbf{y}_{k} - \mathbf{H}_{k}^{x}\hat{\mathbf{x}}_{k+1}^{-}\right) \\ \mathbf{P}_{x|k+1}^{+} &= \left(\mathbf{I} - \mathbf{K}_{k}^{x}\mathbf{H}_{k}^{x}\right)\mathbf{P}_{x|k+1}^{-}\end{aligned} \tag{8}$$

Finally, the measurement-update equations for the motor parameters are:

$$\begin{aligned}\mathbf{K}_{k}^{\theta} &= \mathbf{P}_{\theta|k+1}^{-}\left(\mathbf{C}_{k}^{\theta}\right)^{T}\left(\mathbf{C}_{k}^{\theta}\mathbf{P}_{\theta|k+1}^{-}\left(\mathbf{C}_{k}^{\theta}\right)^{T} + \mathbf{R}_{k}^{\theta}\right) \\ \hat{\boldsymbol{\theta}}_{k+1}^{+} &= \hat{\boldsymbol{\theta}}_{k+1}^{-} + \mathbf{K}_{k}^{\theta}(\mathbf{y}_{k} - \mathbf{H}_{k}^{\theta}\hat{\mathbf{x}}_{k+1}^{-}) \\ \mathbf{P}_{\theta|k+1}^{+} &= (\mathbf{I} - \mathbf{K}_{k}^{\theta}\mathbf{C}_{k}^{\theta})\mathbf{P}_{\theta|k+1}^{-}\end{aligned} \tag{9}$$

Where: $\mathbf{C}_{k}^{\theta}$ can be formulated by the equations (10).

**2.3. Offline parameters initialization**

To begin the recursive computation, the Kalman Filter requires known initial states. If the initial states significantly deviate from the actual value, the initialization error will propagate through recursion as an undiscovered bias [27]. This error causes additional computations during the transient observation, leading to a longer estimation time or cannot converge to the actual value, especially in cases requiring numerous collected samples. In our case, the initial states must be given, including motor output $x_0$ and model parameter $\theta_0$. Where $x_0$ can be known since the initial state of the motor output is usually zero for all different motors and environmental conditions. The initial value of the model parameter $\theta_0$ is more challenging to estimate because $\theta_0$ can vary widely. A systematic approach is therefore needed to give an initial guess for induction motor parameters $\theta_0$. After that, the $\theta_0$ will be adjusted by Dual EKF to improve estimation accuracy.

The stator windings in this paper are ejected with a low DC voltage signal. Then, the least squares method is used to estimate the initial values of the model parameter from the measured currents.

When supply DC voltage ($\omega_m = 0$) to ☞

the stator winding, the dynamic equation from (1) become:

$$\begin{aligned}
\frac{di_{sd}}{dt} &= -\left(\frac{R_s}{L_\sigma} + \frac{R_r L_m^2}{L_r^2 L_\sigma}\right) i_{sd} + \frac{R_r L_m}{L_r^2 L_\sigma}\psi_{rd} + \frac{1}{L_\sigma}v_{sd} \\
\frac{di_{sq}}{dt} &= -\left(\frac{R_s}{L_\sigma} + \frac{R_r L_m^2}{L_r^2 L_\sigma}\right) i_{sd} + \frac{R_r L_m}{L_r^2 L_\sigma}\psi_{rq} + \frac{1}{L_\sigma}v_{sq} \\
\frac{d\psi_{rd}}{dt} &= \frac{R_r}{L_r} L_m i_{sd} - \frac{R_r}{L_r}\psi_{rd} \\
\frac{d\psi_{rq}}{dt} &= \frac{R_r}{L_r} L_m i_{sq} - \frac{R_r}{L_r}\psi_{rq}
\end{aligned} \tag{11}$$

Taking the Laplace transform of equations (11), we can obtain the transfer function for each stator stationary axis component as follows:

$$\frac{I(s)}{U(s)} = \frac{L_r^3 s + L_r^2 R_r}{L_\sigma L_r^3 s^2 + (L_\sigma L_r^2 R_r + R_s L_r^3 + L_m^2 L_r R_r)s + R_r R_s L_r^2} \tag{12}$$

Which has a state space representation as follows:

$$\underbrace{\begin{bmatrix} i_{sd|k+1} \\ i_{sq|k+1} \\ \psi_{sd|k+1} \\ \psi_{sq|k+1} \\ \omega_{m|k+1} \\ \tau_{L|k+1} \end{bmatrix}}_{\mathbf{x}_{k+1}} = \underbrace{\begin{bmatrix} 1-\left(\frac{R_s}{L_\sigma}+\frac{R_r L_m^2}{L_r^2 L_\sigma}\right)t_s & 0 & \frac{R_r L_m}{L_r^2 L_\sigma}t_s & \frac{RL_m}{L_r L_\sigma}p_p\omega_m t_s & 0 & 0 \\ 0 & 1-\left(\frac{R_s}{L_\sigma}+\frac{R_r L_m^2}{L_r^2 L_\sigma}\right)t_s & -\frac{RL_m}{L_r L_\sigma}p_p\omega_m t_s & \frac{R_r L_m}{L_r^2 L_\sigma}t_s & 0 & 0 \\ \frac{R_r L_m}{L_r}t_s & 0 & 1-\frac{R_r}{L_r}t_s & -p_p\omega_m t & 0 & 0 \\ 0 & \frac{R_r L_m}{L_r}t_s & p_p\omega_m t & 1-\frac{R_r}{L_r}t & 0 & 0 \\ -\frac{3}{2}\frac{p_p L_m}{J_L L_r}\psi_{rq}t_s & \frac{3}{2}\frac{p_p L_m}{J_L L_r}\psi_{rd}t_s & 0 & 0 & 1 & -\frac{1}{J_L}t_s \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}}_{\mathbf{A}_k} \underbrace{\begin{bmatrix} i_{sd} \\ i_{sq} \\ \psi_{sd} \\ \psi_{sq} \\ \omega_m \\ \tau_L \end{bmatrix}}_{\mathbf{x}_k} + \underbrace{\begin{bmatrix} \frac{1}{L_\sigma}t_s & 0 \\ 0 & \frac{1}{L_\sigma}t_s \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}}_{\mathbf{B}} \underbrace{\begin{bmatrix} v_{sd} \\ v_{sq} \end{bmatrix}}_{\mathbf{u}_k} + \mathbf{d}_k^{\mathbf{x}}$$

$$\underbrace{\begin{bmatrix} i_{sd} \\ i_{sq} \end{bmatrix}}_{\mathbf{y}_k} = \underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix}}_{\mathbf{H}} \begin{bmatrix} i_{sd} \\ i_{sq} \\ \psi_{sd} \\ \psi_{sq} \\ \omega_m \\ \tau_L \end{bmatrix} + \mathbf{w}_k^{\mathbf{x}}$$

$$\underbrace{\begin{bmatrix} \frac{di_s}{dt} \\ \frac{d^2 i_s}{dt^2} \end{bmatrix}}_{\dot{\mathbf{x}}^{DC}} = \underbrace{\begin{bmatrix} 0 & 0 & 0 & 1 \\ b_0 & b_1 & -a_0 & -a_1 \end{bmatrix}}_{\mathbf{\Theta}} \underbrace{\begin{bmatrix} v_s \\ \frac{dv_s}{dt} \\ i_s \\ \frac{di_s}{dt} \end{bmatrix}}_{\mathbf{x}^e} \tag{13}$$

and the discrete equation with the sampling time $t_s$ has the form of:

$$\mathbf{x}_{k+1}^{DC} = \mathbf{x}_k^{DC} + \mathbf{\Theta}\mathbf{x}_k^e t_s \tag{14}$$

Our objective is to find $\hat{\mathbf{\Theta}}$ from the measurement set of $\mathbf{X}_k^e = \{\mathbf{x}_k^e\}$ and $\mathbf{X}_{k+1}^{DC} = \{\mathbf{x}_{k+1}^{DC}\}$ to minimize the following cost function:

$$J = \frac{1}{2}\left\| \mathbf{X}_{k+1}^{DC} - \mathbf{X}_k^{DC} - \hat{\mathbf{\Theta}}\mathbf{X}_k^e t_s \right\| \tag{15}$$

This is the general least squares problem with the unique solution as follows:

$$\hat{\mathbf{\Theta}} = \begin{bmatrix} 0 & 0 & 0 & 1 \\ b_0 & b_1 & -a_0 & -a_1 \end{bmatrix} = \frac{\mathbf{X}_{k+1}^{DC} - \mathbf{X}_k^{DC}}{t_s}\left(\mathbf{X}_k^e\right)^T\left[\mathbf{X}_k^e\left(\mathbf{X}_k^e\right)^T\right]^\dagger \tag{16}$$

Where $\left[\mathbf{X}_k^e\left(\mathbf{X}_k^e\right)^T\right]^\dagger$ is the pseudo-inverse of $\mathbf{X}_k^e\left(\mathbf{X}_k^e\right)^T$.

If we assume that $L_s \approx L_r$, we can obtain the relatively good initial parameters for the induction motor model by following equations:

$$\begin{aligned}
L_\sigma &= \frac{1}{b_1}, \quad L_s = L_r = \frac{a_1}{b_0} - \frac{a_0 b_1}{b_0^2} \\
R_s &= \frac{a_0}{b_0}, \quad R_r = L_r\frac{b_0}{b_1}, \quad L_m = \left|\sqrt{L_r^2 - L_\sigma L_r}\right|
\end{aligned} \tag{17}$$

Finally, the estimated motor efficiency can be calculated as follows:

$$\mu = \frac{\hat{\tau}_L \hat{\omega}_m}{\sqrt{3}(u_a i_a + u_b i_b + u_c i_c)\cos\vartheta} \tag{18}$$

Where $\cos\vartheta$ is the power factor of 3-phase power line. $[u_a, u_b, u_c]$ and $[i_a, i_b, i_c]$ are the input voltages and currents of 3 stator windings a, b, and c of the induction motor, respectively.

## 3. SIMULATION AND RESULTS

Several simulations are performed to evaluate the feasibility of the proposed framework under various load torque conditions. This paper utilizes a three-phase, four pole, 1.5 kW squirrel cage motor for simulation. The detailed specifications of the induction motor used for simulation are given in Table 1. The sampling rate used for the Dual EKF in the simulation is $t_s = 100\mu s$.

*Table 1. The detailed specifications of the induction motor used for simulation.*

| Rated value | Value | Parameters | Value |
|---|---|---|---|
| $P_{rated}$, kW | 3.0 | $R_s$, Ω | 2.283 |
| f, Hz | 50 | $R_r$, Ω | 2.133 |
| $U_{rated}$, V | 380 | $L_s$, H | 0.233 |
| $I_{rated}$, A | 6.9 | $L_r$, H | 0.231 |
| $n_{rated}$, rpm | 1430 | $L_m$, H | 0.220 |
| $\tau_{rated}$, Nm | 20 | $J_L$, kg.m² | 0.0055 |
| cosϑ | 0.93 | $p_p$ | 2 |

The initial state $x_0$ starts with zero, and the initial parameters $\theta_0$ are obtained from the estimation of offline parameters. The covariance matrix $Q_k$ and $R_k$ are chosen in diagonal form with the values obtained from trial-and-error to achieve a fast convergence rate with low steady-state error. The values of these covariance matrices are given as follows:

$$\begin{aligned}
\mathbf{Q}_k^{\mathbf{x}} &= 10^{-6}\, diag(0.74, 0.74, 0.0074, 0.0074, 60, 1.15) \\
\mathbf{Q}_k^{\theta} &= 10^{-14}\, diag(0.96, 0.96, 0.01, 0.01, 1.0) \\
\mathbf{R}_k^{\mathbf{x}} &= \mathbf{R}_k^{\theta} = 10^{-4}\, diag(0.18, 0.18)
\end{aligned} \tag{19}$$

Figure 2 shows the state estimation results of the proposed framework under the different load torque conditions. The estimated states have a fast convergence rate (setting time $t_{ss} <$ 0.2s) and low steady-state error $(e_{ss}^{x} < 2\%)$ for all states. However, significant errors still remain at the transient state, especially for load torque and rotor speed. These errors are mainly caused by the un-estimated total inertia, directly affecting the motor speed setting time.

$$\mathbf{F}_k \triangleq \frac{\partial \mathbf{f}(\mathbf{x}, \hat{\mathbf{u}}_{k+1}, {}_{k})}{\partial \mathbf{x}}\bigg|_{\mathbf{x}=\hat{\mathbf{x}}_k^{+}} = \begin{bmatrix}
1-\left(\frac{R_s}{L_\sigma}+\frac{R_r L_m^2}{L_r^2 L_\sigma}\right)t_s & 0 & \frac{R_r L_m}{L_r^2 L_\sigma}t_s & \frac{RL_m}{L_r L_\sigma}p_p\omega_m t_s & \frac{RL_m}{L_r L_\sigma}p_p\psi_{rq}t_s & 0 \\
0 & 1-\left(\frac{R_s}{L_\sigma}+\frac{R_r L_m^2}{L_r^2 L_\sigma}\right)t_s & -\frac{RL_m}{L_r L_\sigma}p_p\omega_m t_s & \frac{R_r L_m}{L_r^2 L_\sigma}t_s & -\frac{RL_m}{L_r L_\sigma}p_p\psi_{rd}t_s & 0 \\
\frac{R_r L_m}{L_r}t_s & 0 & 1-\frac{R_r}{L_r}t_s & -p_p\omega_m t & -p_p\psi_{rq}t & 0 \\
0 & \frac{R_r L_m}{L_r}t_s & p_p\omega_m t & 1-\frac{R_r}{L_r}t & p_p\psi_{rd}t & 0 \\
-\frac{3}{2}\frac{p_p L_m}{J_L L_r}\psi_{rq}t_s & \frac{3}{2}\frac{p_p L_m}{J_L L_r}\psi_{rd}t_s & \frac{3}{2}\frac{p_p L_m}{J_L L_r}i_{rq}t_s & -\frac{3}{2}\frac{p_p L_m}{J_L L_r}i_{rd}t_s & 1 & -\frac{1}{J_L}t_s \\
0 & 0 & 0 & 0 & 0 & 1
\end{bmatrix} \tag{7}$$

$$\mathbf{C}_k^{\theta} \triangleq \mathbf{H}_k^{\theta}\frac{\partial \hat{\mathbf{x}}_k^{-}}{\partial \theta}\bigg|_{\theta=\hat{\theta}_{k+1}^{-}} = \begin{bmatrix} \frac{\partial \mathbf{i}_k}{\partial R_s} & \frac{\partial \mathbf{i}_k}{\partial R_r} & \frac{\partial \mathbf{i}_k}{\partial L_s} & \frac{\partial \mathbf{i}_k}{\partial L_r} & \frac{\partial \mathbf{i}_k}{\partial L_m} \end{bmatrix} \tag{10a}$$

$$\begin{aligned}
\frac{\partial \mathbf{i}_{s|k}}{\partial R_s} &= \begin{bmatrix} -\frac{1}{L_\sigma}i_{sd} \\ -\frac{1}{L_\sigma}i_{sq} \end{bmatrix} \\
\frac{\partial \mathbf{i}_{s|k}}{\partial R_r} &= \begin{bmatrix} -\frac{L_m^2}{L_r^2 L_\sigma}i_{sd} + \frac{L_m}{L_r L_\sigma}\psi_{rd} \\ -\frac{L_m^2}{L_r^2 L_\sigma}i_{sq} + \frac{L_m}{L_r L_\sigma}\psi_{rq} \end{bmatrix} \\
\frac{\partial \mathbf{i}_{s|k}}{\partial L_s} &= \begin{bmatrix} \left(\frac{R_s}{L_\sigma^2}+\frac{L_m^2 R_r}{L_r^2 L_\sigma^2}\right)i_{sd} - \frac{L_m R_r}{L_r^2 L_\sigma^2}\psi_{rd} - \frac{L_m}{L_r L_\sigma^2}p_p\omega_m\psi_{rq} - \frac{1}{L_\sigma^2}v_{sd} \\ \left(\frac{R_s}{L_\sigma^2}+\frac{L_m^2 R_r}{L_r^2 L_\sigma^2}\right)i_{sq} - \frac{L_m R_r}{L_r^2 L_\sigma^2}\psi_{rq} + \frac{L_m}{L_r L_\sigma^2}p_p\omega_m\psi_{rd} - \frac{1}{L_\sigma^2}v_{sq} \end{bmatrix} \\
\frac{\partial \mathbf{i}_{s|k}}{\partial L_r} &= \begin{bmatrix} \left(\frac{L_m^2 R_s}{L_r^2 L_\sigma^2}+\frac{L_m^2 R_r\left(L_s+L_\sigma\right)}{L_r^3 L_\sigma^2}\right)i_{sd} - \frac{L_m R_r\left(2L_s L_r - L_m^2\right)}{L_r^4 L_\sigma^2}\psi_{rd} - \frac{L_s L_m}{L_r^2 L_\sigma^2}p_p\omega_m\psi_{rq} - \frac{L_m^2}{L_r^2 L_\sigma^2}v_{sd} \\ \left(\frac{L_m^2 R_s}{L_r^2 L_\sigma^2}+\frac{L_m^2 R_r\left(L_s+L_\sigma\right)}{L_r^3 L_\sigma^2}\right)i_{sq} - \frac{L_m R_r\left(2L_s L_r - L_m^2\right)}{L_r^4 L_\sigma^2}\psi_{rq} + \frac{L_s L_m}{L_r^2 L_\sigma^2}p_p\omega_m\psi_{rd} - \frac{L_m^2}{L_r^2 L_\sigma^2}v_{sq} \end{bmatrix} \\
\frac{\partial \mathbf{i}_{s|k}}{\partial L_m} &= \begin{bmatrix} -\left(\frac{2L_m R_s}{L_r L_\sigma^2}+\frac{2L_s L_m R_r}{L_r^3 L_\sigma^2}\right)i_{sd} + \frac{R_r\left(L_s L_r + L_m^2\right)}{L_r^3 L_\sigma^2}\psi_{rd} + \frac{L_s L_r + L_m^2}{L_r^2 L_\sigma^2}p_p\omega_m\psi_{rq} + \frac{2L_m}{L_r L_\sigma^2}v_{sd} \\ -\left(\frac{2L_m R_s}{L_r L_\sigma^2}+\frac{2L_s L_m R_r}{L_r^3 L_\sigma^2}\right)i_{sq} + \frac{R_r\left(L_s L_r + L_m^2\right)}{L_r^3 L_\sigma^2}\psi_{rq} - \frac{L_s L_r + L_m^2}{L_r^2 L_\sigma^2}p_p\omega_m\psi_{rd} + \frac{2L_m}{L_r L_\sigma^2}v_{sq} \end{bmatrix}
\end{aligned} \tag{10b}$$

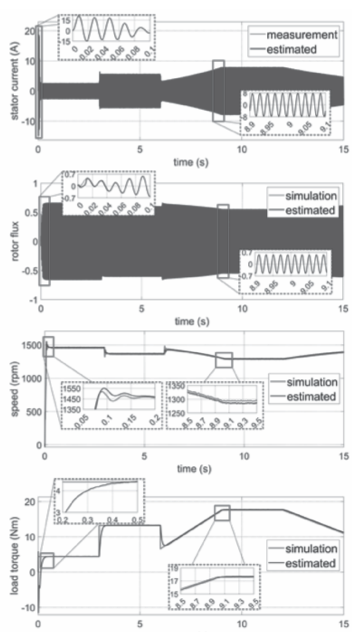


*Figure 2. The state estimation results of the proposed framework*

In Figure 3, the initial parameters estimated by the proposed offline initialization method already have a good estimation accuracy $(e_{ss}^{\theta} < 2\%)$. Compared to the framework without initialization, the proposed method can archive faster converge rate for the parameters estimation problem, leading to improved settling time and settlement error for the state estimation problem.

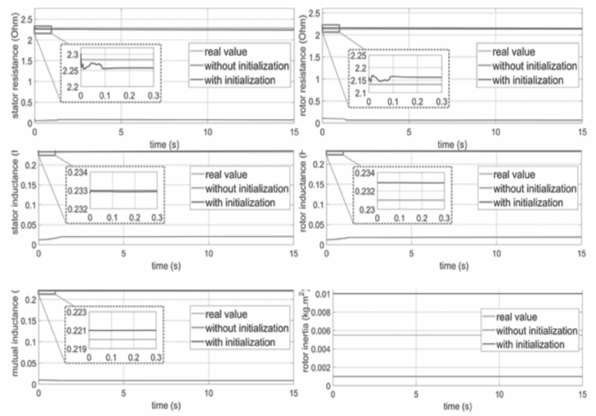

*Figure 3. The parameters estimation results under the proposed offline parameters initialization.*

Figure 4 shows the efficiency estimation result of the proposed framework. The steady state errors remained below 2% in all cases with the settling time less than 0.5s. The estimated efficiency also produces good transient errors for cases where the load torque does not change suddenly (t = 9s and t = 12s).

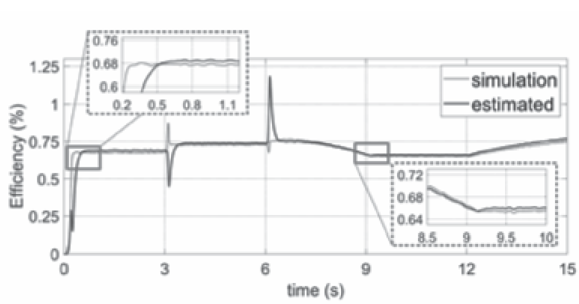


*Figure 4. The efficiency estimation result of the proposed framework.*

## 4. CONCLUSIONS

The aim of this paper is to present a comprehensive framework that relies on the Dual Extended Kalman Filter to estimate the efficiency of 3-phase induction motors. The least squares method parameter initialization is integrated to guarantee fast convergence response and settling time. The proposed framework only requires measurements of stator current and voltage at the electrical terminal box. The simulation results show that the proposed framework can achieve steady state errors below 2% for motor efficiency estimation problems with acceptable settling time ($t_{ss}$ = 0.5s). This result holds promise for developing algorithms based on the health index for industrial predictive maintenance applications. In addition, estimating total inertia remains an issue that needs to be resolved to improve settling time and transient errors.

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