Stator resistance estimation scheme using fuzzy logic system for direct torque controlled induction motor drive

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Abstract. Direct Torque controlled induction motor (DTC-IM) drives have been used widely over last few decades. DTC-IM drives use the stator resistance of the motor for stator flux estimation which directly depends on the stator resistance of IM. Proper estimation of the stator resistance is very important because stator resistance varies due to the increase in temperature of the machine during operation. An online estimation of the stator resistance of the induction motor using model reference adaptive system (MRAS) and fuzzy logic for the direct torque control drive is modeled and verified in this paper. The error between the actual state variable of the machine and the estimated value of the reference model and rate of change of this error is used as input by the fuzzy estimator which gives the change in resistance value as output. From simulation it has been proved that the estimator can track the stator resistance value within 70 ms when a step change of stator resistance has been applied. The efficacy of the estimator is investigated in simulation by varying the stator resistance from the nominal value which has been done in MATLAB/SIMULINK.

Keywords: Direct torque control, induction motor, stator resistance, MRAS, fuzzy logic

1. Introduction

To achieve the high performance of the induction motor drive proper estimation of the stator flux is needed. Due to variation of the temperature throughout the operation of the induction motor stator resistance varies continuously [1]. Variation of the stator resistance introduces error in estimated flux position and magnitude of the stator flux [2]. Error in the estimated stator flux deteriorates the performance of DTC drive. The effect of error in estimation is very important mainly at low speed [2].

Recently many approaches have been reported to estimate the accurate value of the stator resistance of the induction motor when the motor operates in DTC drives. Stator resistance estimation schemes developed so far can be broadly classified under some distinct categories. Generally all of the schemes depend on stator voltage (reconstructed or measured) and measured stator current.

All schemes which use steady state induction motor model and some measured quantities to calculate explicitly the stator resistance [3–8] can be categorized as the first group. In [3] reactive power is evaluated using measured terminal variables, rotor and stator flux is evaluated next and then drive torque is evaluated. Finally an expression is derived to calculate stator resistance as a function of the previously evaluated...
quantities. The scheme addressed in [4] is mainly based on back electromagnetic force (BEMF) detector. In this strategy the stator resistance calculation has been done in reference frame which aligned with stator current vector. In [5] stator voltage model has been used to calculate stator resistance. Stator resistance is evaluated from active power balance of machine in [6].

The second category of the stator resistance estimation schemes is the most frequently used which includes estimators where the value of stator resistance is updated through the adaptive mechanism [9–20]. For this purpose integral (I) or proportional-integral (PI) controllers are being used. In principle, different two subgroups exist. In the observer based system [11, 12, 14, 17, 18, 21] error quantity worked as input to the adaptation mechanism of the stator resistance determination using difference between the measured and observed current signal. In this field extended Kalman filter is mostly used because of its robustness and also it requires less number of PI controllers [22–25].

In model reference adaptive system (MRAS) [9, 10, 13, 15, 16, 19, 26] error quantity selection is more diverse. The method addressed in [9] operates in the rotating coordinate system and error determination is accomplished with difference between d-axis rotor flux obtained from voltage and current models. The method proposed in [10] is almost same but it uses rotor flux reference and one model is used to determine d-axis component of rotor flux to form the error. Error signal in [19] is mainly based on the active power but in [13] it is found as the sum of the products of rotor flux and rotor current d and q-axis components. Error signal of [16] uses an error in d-axis stator current component as input of integral controller, while error signal of [17] is obtained in such a way that identification of stator resistance is totally independent of leakage inductance. The model reference adaptive controller (MRAC) proposed in [26] is formed with the use of steady state and instantaneous values of a fictitious quantity which has no physical significance.

The third group of the stator resistance identification techniques depends on the utilization of the artificial intelligence schemes in the adaptation mechanism of stator resistance [27–35]. Fuzzy logic control (FLC) [29, 30, 33], artificial neural network (ANN) [27, 32, 34], or neuro-fuzzy control can be applied for this goal.

In the classical control methods, knowledge of the controlled system is needed in a form of the set of differential and algebraic equations, which relate outputs and inputs analytically. However model used in the classical control methods can be complex, depends on some assumptions, may use parameters which are not easily measurable. The classical control theory has some limitations because of the assumptions which are being made for the control system such as linearity, time invariance etc. These limitations can be solved by using control schemes which based on artificial intelligence and these schemes can also be used even the analytical models are unknown. Such types of control techniques are less sensitive to the parameter variation compare to the classical control techniques.

One of the main advantage of fuzzy estimator is the capability of approximating nonlinear function relationship. In this paper effect of the change in stator resistance is discussed and an online fuzzy stator resistance estimator is addressed to estimate the accurate value of stator resistance and also the efficacy of the estimator is shown.

An online stator resistance estimator using a model reference adaptive system (MRAS) with fuzzy logic has been presented in this paper. This paper has organized in five sections. DTC principle is presented in the following section. Proposed stator resistance estimation technique is given in Section 3. Simulation results are described in Section 4. Finally conclusion is presented in Section 5.

2. DTC principle

In DTC shown in Fig. 1 errors of the electromechanical torque and stator flux status is detected then passed through the hysteresis comparator (two and three levels) for digitization. Then a predetermined switching table given in Table 1 determine the status of the inverter switches which will be used to determine voltage space vector (Vs) location which actually depends on the stator flux angle. Torque and flux hysteresis comparator output is denoted as \( \Delta T \) and \( \Delta \psi \) respectively, and also flux linkage sector is indicated as S. Torque reference \( T_c \) and stator flux reference amplitude \( \psi_s \) are compared with estimated values of torque and stator flux. Torque error \( e_T \) and flux error \( e_\psi \) are passed through the three and two level comparator respectively. Digitized output \( \Delta \psi_s \) and \( \Delta T \), stator flux position vector decides appropriate voltage from selection table. Signal \( \Delta T \) can be defined as follows:

\[
\Delta T = \begin{cases} 
1 & \text{for } e_T > H_T \\
0 & \text{for } e_T = T_c \\
1 & \text{for } e_T < -H_T 
\end{cases}
\]

\[
\Delta T = \begin{cases} 
1 & \text{for } e_\psi > H_\psi \\
0 & \text{for } e_\psi = \psi_s \\
1 & \text{for } e_\psi < -H_\psi 
\end{cases}
\]
Fig. 1. Basic IM-DTC drive.

Table 1

<table>
<thead>
<tr>
<th>ΔΨ</th>
<th>ΔT</th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
<th>S4</th>
<th>S5</th>
<th>S6</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>V3</td>
<td>V5</td>
<td>V2</td>
<td>V4</td>
<td>V1</td>
<td>V6</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>V5</td>
<td>V1</td>
<td>V3</td>
<td>V6</td>
<td>V4</td>
<td>V2</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>V6</td>
<td>V2</td>
<td>V4</td>
<td>V1</td>
<td>V3</td>
<td>V5</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>V6</td>
<td>V1</td>
<td>V4</td>
<td>V5</td>
<td>V3</td>
<td>V2</td>
</tr>
</tbody>
</table>

And signal Δψ₁ as:

\[
ΔΨ₁ = \begin{cases} 
1 & \text{for } eₘ > Hₚ \\
0 & \text{for } eₘ > -Hₚ 
\end{cases}
\]  

(4)

(5)

With the reference to Table 1, if \( eₘ \) is greater than the upper flux hysteresis band then ΔΨ₁ will be 1 and if \( eₘ \) is greater than the upper torque hysteresis band then ΔT will be 1. During this time if the stator flux vector is in sector 1 then \( V₁ (1 1 0) \) will be selected to minimize the torque and flux error.

The stator flux is given by the following equation:

\[
ψₘ = \int (Vᵢ - Rᵢiᵢ) \, dt
\]  

(6)

So \( d \) and \( q \) axis stator flux can be given as:

\[
ψₘ = \int (Vᵢ - Rᵢiᵢ) \, dt
\]  

(7)

\[
ψₘ = \int (Vᵢ - Rᵢiᵢ) \, dt
\]  

(8)

Electromagnetic Torque

\[
T = \frac{3}{2} p (ψₘiₚₚ - ψₘiₚₚ)
\]  

(9)

According to the basic DTC strategy stator flux is estimated by integrating the back emf as stated in Equation (6) and electromagnetic torque estimation can be done by Equation (9).

From Equation (6) it has been seen that variation of the stator resistance will cause to change the stator flux which will in turn affect the estimated torque, which will deteriorate the effectiveness of the robustness and faster response of the DTC which is illustrated in Fig. 2.

3. Fuzzy stator resistance estimator

The structure of the fuzzy logic estimator of the stator resistance of the DTC-IM drive is described in Fig. 3

Voltage model

\[
\frac{dψᵢₚₚ}{dt} = \frac{Lₚ}{Lₚ} \left( Vᵢₚₚ - Rᵢₚₚ - σLₚ \frac{diₚₚ}{dt} \right)
\]  

(10)

\[
\frac{dψᵢₚₚ}{dt} = \frac{Lₚ}{Lₚ} \left( Vᵢₚₚ - Rᵢₚₚ - σLₚ \frac{diₚₚ}{dt} \right)
\]  

(11)

Current model

\[
\frac{dψₚₚ}{dt} = \frac{1}{Tᵢ} \left( Lₚ iₚₚ - ψₚₚ - ωrTrψₚₚ \right)
\]  

(12)

\[
\frac{dψₚₚ}{dt} = \frac{1}{Tᵢ} \left( Lₚ iₚₚ - ψₚₚ + ωrTrψₚₚ \right)
\]  

(13)

Fig. 2. Effect of the variation of stator resistance on the DTC drive.
can be found as follows

$$\sigma L_s q_s = v_{ds} - R_s i_{ds} - L_s \frac{d i_{ds}}{dt} - \omega_r L_m i_{qr} - \sigma L_s \left( k - 1 \right)$$

(14)

Using the discrete form of the above equation

$$\sigma L_s q_s = v_{ds} - R_s i_{ds} - \frac{L_s}{\Delta t} \left( i_{ds}(k) - i_{ds}(k-1) \right) - \frac{L_m}{\Delta t} \left( i_{qr}(k) - i_{qr}(k-1) \right) + \frac{L_m}{\Delta t} \omega_r \psi_{im}(k)$$

(15)

From Equation (15) estimated d-axis stator current can be found as follows

$$i_{ds}(k) = \left( \frac{T_s}{\sigma L_s} \right) v_{ds}(k) - \left( k - 1 \right) + \left( \frac{T_s}{\sigma L_s} \right) \left[ L_m \frac{d i_{qr}}{dt} + \frac{L_m}{\Delta t} \omega_r \psi_{im} \right]$$

(16)

Equation (16) can be represented using the coefficients $W_1, W_2, W_3, W_4$ as follows

$$i_{ds}(k) = W_1 \psi_{im}(k-1) + W_2 \psi_{im}(k-1) + W_3 \left( \frac{L_m}{\Delta t} \omega_r \psi_{im} \right) + W_4 \left( \frac{T_s}{\sigma L_s} \right) \left[ L_m \frac{d i_{qr}}{dt} + \frac{L_m}{\Delta t} \omega_r \psi_{im} \right]$$

(17)

Table 2

<table>
<thead>
<tr>
<th>Rule base of the fuzzy estimator of the stator resistance</th>
</tr>
</thead>
<tbody>
<tr>
<td>LN</td>
</tr>
<tr>
<td>----------------</td>
</tr>
<tr>
<td>LN</td>
</tr>
<tr>
<td>MN</td>
</tr>
<tr>
<td>Z</td>
</tr>
<tr>
<td>SP</td>
</tr>
<tr>
<td>MP</td>
</tr>
<tr>
<td>LP</td>
</tr>
</tbody>
</table>

Here,

$$W_1 = \left( \frac{T_s}{\sigma L_s} \right) \left( \frac{L_m}{\Delta t} \omega_r \psi_{im} \right)$$

$$W_2 = \left( \frac{T_s}{\sigma L_s} \right) \left( \frac{L_m}{\Delta t} \omega_r \psi_{im} \right)$$

$$W_3 = \left( \frac{T_s}{\sigma L_s} \right) \left( \frac{L_m}{\Delta t} \omega_r \psi_{im} \right)$$

$$W_4 = 1 - \left( \frac{T_s}{\sigma L_s} \right) \left( \frac{L_m}{\Delta t} \omega_r \psi_{im} \right)$$

(18)

The relation between the stator current and stator resistance is non-linear [37], so it is possible to map it easily using a fuzzy system.

Proposed Fuzzy logic estimator used to estimate the change in stator resistance is shown in Fig. 3. The error $e(k)$ between the estimated $i_{ds}(k)$ and measured d-axis stator current $i_{ds}(k)$ and rate of change of the error $\Delta e(k)$ is used for the estimation of the changing value of the stator resistance through the fuzzy estimator.

$$e(k) = \Delta i_{ds} = i_{ds}(k) - i_{ds}(k-1)$$

(19)

The incremental value of the stator resistance ($\Delta Rs$) is continuously added to the previous value of the stator resistance $Rs$.

There are two input variables for the fuzzification stage which are $e(k)$ and $\Delta e(k)$ and the output is $\Delta Rs$. They are divided into seven fuzzy segments named as Large Negative (LN), Medium Negative (MN), Small Negative (SN), Zero (Z), Large Positive (LP), Medium Positive (MP), and Small Positive (SP).

The crisp input variables have been converted to the fuzzy variables using the triangular membership functions given in the Fig. 4a and b.

The control range is $-0.3$ to $0.3$ A for the current error and $-0.25$ to $0.25$ for the change in current error. Fuzzy rules used for the estimator are shown in Table 2.

In the defuzzification stage, the output $\Delta Rs$ is found by using Mean of Maximum (MoM) operator. Membership function used in this stage is shown in Fig. 4c.
4. Results

The effectiveness of the proposed fuzzy stator resistance estimator has been verified in Matlab/Simulink. Control surface of the fuzzy stator resistance estimator is shown in Fig. 5.

Fig. 5. Control surface of the fuzzy estimator.

Fig. 4. a) Membership distribution for the d-axis current error, b) Membership distribution for the change in d-axis current, c) Membership distribution for the change in resistance.

Fig. 6. Stator resistance variation effect. (a) step variation of the stator resistance, (b) speed (rpm), (c) electromagnetic torque (N-m) (d) Stator flux locus.

Induction motor parameters used in the simulation are given in Table 4. The torque reference is found from the speed controller. A PI controller is used as speed controller. Flux reference used in the simulation is 0.9 Wb. An initial load torque of 10 Nm is used.

Stator resistance may vary up to 50% during operation of the motor due to the change in temperature.
Fig. 7. Compensation of the Stator resistance variation effect. (a) step variation of the stator resistance, (b) zoomed view of stator resistance tracking, (c) motor speed (rpm), (d) electromagnetic torque (N-m), (e) Stator flux locus.

Table 3

<table>
<thead>
<tr>
<th>Indicators Estimators</th>
<th>Overshoot</th>
<th>Steady state</th>
<th>Settling error</th>
<th>Time(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PI [38]</td>
<td>25.33%</td>
<td>Zero</td>
<td>0.16</td>
<td></td>
</tr>
<tr>
<td>Neuro-Fuzzy [38]</td>
<td>2.5%</td>
<td>0.0004</td>
<td>0.14</td>
<td></td>
</tr>
<tr>
<td>Adaptive Observer [39]</td>
<td>No overshoot</td>
<td>Tends to zero</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Stator resistance</td>
<td>Present</td>
<td>Present</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adaptation [40]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reduced order EKF [24]</td>
<td>No</td>
<td>0.3</td>
<td>0.07</td>
<td></td>
</tr>
<tr>
<td>Proposed Fuzzy Estimator</td>
<td>No</td>
<td>0.001</td>
<td>0.07</td>
<td></td>
</tr>
</tbody>
</table>

Table 4

<table>
<thead>
<tr>
<th>Induction motor parameter</th>
<th>Rated Power (kW)</th>
<th>Rotor Resistance (Ω)</th>
<th>Rated Voltage (V)</th>
<th>Stator Inductance (H)</th>
<th>Pole Pair</th>
<th>Magnetizing Inductance (H)</th>
<th>Rotor Resistance (Ω)</th>
<th>Rated Speed (rpm)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>3.7</td>
<td>1.083</td>
<td>460</td>
<td>0.209674</td>
<td>2</td>
<td>0.2037</td>
<td>1.115</td>
<td>1750</td>
</tr>
</tbody>
</table>

Therefore, stator resistance has been increased at 1.0 sec. from 1.115 Ω to 1.3 Ω to validate the effectiveness of the fuzzy estimation scheme which is given in Fig. 6a. In the conventional system fixed value of the stator resistance is used. Therefore the speed becomes unstable given in Fig. 6b and there are more ripples in the output torque illustrated in Fig. 6c when changing the stator resistance take place. From stator flux locus we can see that there are much more ripples around the expected stator flux presented in Fig. 6d.

From Fig. 7a it can be seen that the estimated value of the proposed estimator can track the actual value of the stator resistance within 70 ms which is shown in the zoomed view of the stator resistance tracking given in Fig. 7b. Torque and flux ripples are reduced after using the proposed estimator though the stator resistance has been changed as presented in Fig. 7d and e respectively and also speed becomes stable after introducing the stator resistance estimator which is shown in Fig. 7c. These
results prove the effectiveness of the proposed technique. The estimated resistance converges very well to the actual value. As a result torque and flux ripple is minimized.

A comparative study between the estimator proposed in this paper and estimator proposed in [24, 38–40] have been presented in terms of overshoot, steady state error and settling time which is given in Table 3.

5. Conclusion

A new on-line stator resistance estimation technique for the DTC-IM drive is addressed in this paper using a fuzzy logic system. It has been proved that fuzzy estimator can detect changes of the stator resistance and also the estimator can converge to stator resistance steady state value within 70 milliseconds. From Table 3 it has been confirmed that proposed estimator is better than the estimators proposed previously as there is no overshoot and also small steady state error. Simulation results reveal that the proposed fuzzy estimator is excellent to estimate the stator resistance in on-line. Utilization of this estimator facilitates the development of a DTC-IM drive system with reduced torque and flux ripple at different operating condition of the motor. Utilization of this estimator enables the improvement of a DTC-IM drive system with reduced torque and flux ripple at different operating condition of the motor.

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**Appendix**

**Symbols & Meaning**

\[ \begin{align*}
 & d \text{ & q axis rotor flux linkages estimated } \\
 & \psi_{dm} \text{ & } \psi_{qm} \\
 & \sigma \text{ Leakage factor (1 - } \frac{L_s}{L_r}) \\
 & i_{ds} \text{ d-axis stator current } \\
 & T_s \text{ Sampling Time } \\
 & T_r \text{ Rotor Time Constant } \\
 & L_s \text{ & } L_r \text{ Stator & Rotor Inductance Respectively }
\end{align*} \]