Speed Observer Design for Linear Induction Motor Drives

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Abstract:
In this paper, a neural network model reference adaptive system speed observer is designed, which can be used in speed control of linear induction motors (LIMs). Dynamical equations of LIM have been considered accurate. In other words, the end effect and the electrical losses of the motor have been included in the motor equivalent circuit. Then equations of the reference model and adaptive model have been extracted. Existence of the speed-dependent functions in the reference model causes error in speed estimation. In order to reduce error, the reference model equations are updated unlike the standard MRAS method. The adaptive model equations have also been discrete and they have been rewritten so as to be represented by a linear neural network (ADALINE). On this basis, the so-called back propagation has been used to compute online, in recursive form, the machine linear speed. Finally, the estimated speed is used for motor speed control. The simulations show the efficiency of the method.

Keywords: electrical railway, linear induction motor, sensorless control, speed estimation
1- Introduction
Linear induction motors (LIM) are linear rotating induction motors counterpart in which the input electrical power is converted into mechanical power with a linear motion. These machines that have special abilities and characteristics are suitable for using in industrial with linear motion. The most important feature of these motors is that they don’t need gear to produce linear motion (Gieras, 1994). A conceptual construction of a LIM that is used in linear metro is depicted in Fig.1.

Despite the advantages such as high start thrust force, and lower loss, the electrical structure of LIMs is more complex than RIMs and this is due to high electromagnetic coupling between flux and torque and a phenomenon called “end-effect”. This phenomenon is due to the asymmetric structure of LIM rather than RIM that makes the control of motor more difficult (Xu et al., 2009; Rathore and Mahendra, 2004; Lin et al., 2006; Yu, 2007).

In order to control the speed of LIM, a linear encoder is required that is usually more costly and less reliable than corresponding counterpart in the rotating machine. In addition, in the LIM case, the cost of sensors increases with increasing the length of the induced part, and the price often is higher than LIM (Cirrincione et al., 2013). Because of this, it limits application of these motors in industries such as railways traction systems.

Another disadvantage of the sensor is that due to their location of installation, they are exposed to environmental factors such as humidity and mechanical stress. So the suitable sensorless approach for the speed control of LIM is very interesting (Huang et al., 2008). Generally, a good estimation of the speed or position of an AC motor still has a lot of problems. Various methods have been used to estimate the speed and the flux of RIM, but a few of them have been used for LIM. This is due to the high complexity of the motor and probably hard observability of motor speed which the end-effect of the LIM is considered also (Cirrincione et al., 2013). However, among a few papers that have noted the issue of sensorless control of LIM, (Cirrincione et al., 2013; Huang et al., 2008; Ryu et al., 2000; Gadoue et al., 2008; Da Silva et al., 2003) can be referred. (Huang et al., 2008) has proposed an adaptive speed sensorless controller with high complexity. A sensorless method based on high-frequency signal injection has been proposed in (Ryu et al., 2000). (Gadoue et al., 2008) Presents an experimental evaluation of the performance of MRAS speed observer while working at very low and zero speed. (Cirrincione et al., 2013) has proposed an observer of neural network model reference adaptive system (NN MRAS). Adaptation mechanism in this method is TLS EXIN. The problem of performing of MRAS method is not to consider Q for LIM. In this paper, we propose a method that can be used the accurate equations of reference model.

After this brief introduction, the paper aims to provide information organized in the following sections. Section II presents the principle of equivalent circuit of the LIM. Section III covers the basis field oriented control for the LIM. Section IV proposes the observer structure. Simulation results and conclusion are presented in sections V and VI respectively.

Nomenclature

<table>
<thead>
<tr>
<th>s, r</th>
<th>Primary and secondary subscript respectively</th>
<th>$\omega_r$</th>
<th>Rotor angular frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>q, d</td>
<td>Subscript related to q-, and d-axis</td>
<td>$\psi_{sd}, \psi_{sq}$</td>
<td>Primary flux</td>
</tr>
<tr>
<td>$L_{lr}, L_{ls}$</td>
<td>Primary and secondary leakage inductances</td>
<td>$\psi_{rl}, \psi_{rq}$</td>
<td>Secondary flux</td>
</tr>
<tr>
<td>$L_m$</td>
<td>Magnetizing inductance</td>
<td>$n_p$</td>
<td>Pole number</td>
</tr>
<tr>
<td>$U_{sd}, U_{sq}$</td>
<td>Primary voltages</td>
<td>$l$</td>
<td>Primary length</td>
</tr>
<tr>
<td>$U_{rd}, U_{rq}$</td>
<td>Secondary voltages</td>
<td>$\tau$</td>
<td>Pole pitch</td>
</tr>
<tr>
<td>$i_{sd}, i_{sq}$</td>
<td>Primary electrical currents</td>
<td>$R_r, R_s$</td>
<td>Primary and secondary resistances</td>
</tr>
</tbody>
</table>
2- Equivalent circuit of the LIM

The moveable part of LIM is called primary (inductor part), and the stationary part is called secondary (inducted part). The primary usually contains a three phase winding in the uniform slots of the laminated core and the secondary is made of an aluminum or copper sheet with or without a solid back iron core (Cirrincione et al., 2013). Since the primary and the secondary of LIM have finite lengths, flux conditions in start and end edges of the inductor element will change due to motion in inductor. So, this will cause a considerable effect on dynamic and static performances of machine conditions, especially at higher speeds. In other words, if the inductor moves on the induced part surface, a magnetic field will appear at the beginning of inductor. Also, the magnetic field at the end of the inductor will be eliminated, gradually. These flux variations produce magnetic field in the secondary surface and beneath edges of stator which deviates the actual net flux distribution in the air gap. This phenomenon is known as end-effect which is reported in (Da Silva et al., 2003; Liu et al., 2006; Fujii et al., 2006). In the literature, end-effect phenomenon is formulated as

\[ Q = \frac{R_r l}{L_m + L_{Lr}} \]

called end-effect factor. This factor was firstly introduced by Duncan (Duncan, 1983). He derived useful function expression \( f(Q) \) according to secondary eddy current average value applying an energy conversion balance theorem. Considering end-effect in the Dynamic Model of the LIM does in two ways. In other words in the literature, two equivalent circuits have been presented for LIM.

The first dynamic model is based on T-model equivalent circuit of Rotational Induction Motor (RIM) assuming the end-effect. This model was firstly presented by Duncan in (Duncan, 1983). He indicated that the end-effect only affected the d-axis equivalent circuit of LIM while the q-axis equivalent circuit is equal to RIM.

The second dynamic model of LIM assuming the end-effect has been introduced in (Kang and Nam 2005). It is based on symmetrical d-q axis models considering the mutual inductance influenced by the eddy current, regardless of the effect of secondary resistance. The eddy current loss which is modeled with \( R_{eddy} \) is neglected and only Duncan’s magnetizing inductance is considered.

It should be noted that in this paper, the second model of LIM has been used, but eddy current losses have not been ignored and a resistor has been considered series with the magnetic branch.

3- Field oriented control based on secondary flux for the LIM

The driving principles of the LIMs are similar to the RIMs, but its control characteristics are more complicated than the RIM (Gadoue et al., 2008; Da Silva et al., 2003). Field oriented control (FOC) is well known in advanced control scheme. It has an excellent dynamic performance mainly due to the decoupled control of inductor magnetic field and thrust force similar to the direct current motor drive. The aim of FOC is to maintain constant the d-axis secondary flux and makes zero the q-axis secondary flux.

There are two types of FOC for LIM drive: indirect-FOC (IFOC) and direct-FOC (DFOC). DFOC directly measures or estimates the location of secondary flux axis, and utilizes the field angle to decouple the stator currents into quadrature and direct components, \( i_{qs} \) and \( i_{ds} \) are called thrust and magnetizing current, respectively.

The concept of IFOC is similar to DFOC in which the
position of secondary flux is calculated using the motor equations. The major drawbacks of IFOC scheme is that it dependents on motor parameters and load disturbance since the model of the machine is used for flux angle calculation (Lipo, 1996). A general block diagram of a LIM drive with DFOC is shown in Fig. 3. It should be noted that in this paper the angular secondary flux position for direct field oriented control is estimated by the NN MRAS.

![Figure 3. Block diagram of the DFOC](image)

**4- Structure of the observer**

Model reference adaptive system is one of the conventional methods for estimating the speed and flux of RIM. MRAS has a variety of Methods, each of which has been used for RIM, but these methods have been used less for LIM because it is more complicated than RIM. All of the MRAS-based speed estimation designs contained a reference model and also an adaptive model. In the traditional MRAS the inputs of the adaptive model is the estimated motor speed and the primary currents. The estimated motor speed is the output of a proper adaption mechanism, which utilized at its inputs of the estimated state variables of the reference and adaptive models. The important differences between the different traditional MRAS-based speed estimator designs lie basically in the kind of speed tuning signal used.

Larger accuracy and robustness can be achieved if mathematical model for the adaptive model is not used at all and instead, an artificial-intelligent-based adaptive model is employed. It is then also possible to eliminate the need for the separate PI controller, since this can be integrated into the tuning mechanism of appropriate artificial-intelligence-based model. (Yu, 2007) has presented a NN MRAS observer in which reference equation contains the function \( f(Q) \), but due to unavailability of the speed of this function has been forgot in the reference model and in order to compensate it, learning law has used more complex than error back propagation (BP).

Using the primary equations of LIM, reference model equations can be written as follows:

\[
\frac{L_{im}(1-f(Q))}{L_{lr}+L_{m}(1-f(Q))} \psi_{rd} = U_{sd} - R_{s}i_{sd} - L_{is} \frac{R_{r}f(Q)}{L_{m}(1-f(Q))} \psi_{rd} \tag{1}
\]

\[
\frac{L_{im}(1-f(Q))}{L_{lr}+L_{m}(1-f(Q))} \psi_{rq} = U_{sq} - R_{s}i_{sq} - L_{is} \frac{R_{r}f(Q)}{L_{m}(1-f(Q))} \psi_{rq} \tag{2}
\]

Regardless of the secondary leakage inductance (1) and (2) can be changed as follows:

\[
\frac{d\psi_{rd}'}{dt} = U_{sd} - R_{s}i_{sd} - L_{is} \frac{R_{r}f(Q)}{L_{m}(1-f(Q))} \psi_{rd}' \tag{3}
\]

\[
\frac{d\psi_{rq}'}{dt} = U_{sq} - R_{s}i_{sq} - L_{is} \frac{R_{r}f(Q)}{L_{m}(1-f(Q))} \psi_{rq}' \tag{4}
\]

As it is seen in the equations (3) and (4), the function \( f(Q) \) is present that it have been removed in (Yu, 2007). This causes the error between the output of the reference model and the adaptive model. In this paper, equations of the reference model such as equations of the adaptive model updates. A diagram of this method is shown in Fig. 4.

The adaptive model equations are also obtained by using the secondary equations, which is simplified as follows:

\[
\frac{d\psi_{rd}'}{dt} = R_{r}i_{rd} + \omega_{r} \psi_{rd}' - R_{r}f(Q) \psi_{rd}' \tag{5}
\]

\[
\frac{d\psi_{rq}'}{dt} = R_{r}i_{sq} + \omega_{r} \psi_{rd}' - R_{r}f(Q) \psi_{rq}' \tag{6}
\]

These equations can be used as an adaptive model, because they explicitly dependent on speed. The adaptive model is written as a function of the electri-
cal rotating speed of the LIM instead of the linear speed, being the relationship between the two the following:
\[
\omega_s = \left(\frac{\pi}{T_p}\right) v
\]  
(7)

The discretization of these equations with using Euler method can be obtain equations of an ADALINE (linear neural network).

\[
\psi_{rd}(k) = \psi_{rd}(k-1) + R_r T_s i_{sd}(k-1) - \frac{\pi T_e}{\tau_m} v(k-1) \psi_{rq}(k-1) - \frac{R_r T_s (1+f(Q))}{L_m (1-f(Q))} \psi_{rd}(k-1)
\]  
(8)

\[
\psi_{rq}(k) = \psi_{rq}(k-1) + R_r T_s i_{sq}(k-1) - \frac{\pi T_e}{\tau_m} v(k-1) \psi_{rd}(k-1) - \frac{R_r T_s (1+f(Q))}{L_m (1-f(Q))} \psi_{rq}(k-1)
\]  
(9)

Which \(k\) and \(T_s\) are current time sample and sampling time respectively. These equations can be rewritten in this way:
\[
\hat{\psi}_{rd}(k) = \omega_1 \psi_{rd}(k-1) - \omega_2 \psi_{rq}(k-1) + \omega_3 i_{sd}(k-1)
\]  
(10)

\[
\hat{\psi}_{rq}(k) = \omega_1 \psi_{rq}(k-1) + \omega_2 \psi_{rd}(k-1) + \omega_3 i_{sq}(k-1)
\]  
(11)

Equations (10) and (11) are an ADALINE with four inputs and two outputs in which their weights are defined as follows:
\[
\omega_1 = 1 - \frac{R_r T_s (1+f(Q))}{L_m (1-f(Q))}, \quad \omega_2 = \frac{p\pi T_e}{\tau_p} v(k-1), \quad \omega_3 = R_r T_s
\]  
(12)

It should be remarked that the flux inputs of the artificial neural network (ANN) are coming from the reference model and not from adaptive one. Therefore the NN is not used in the usual “simulation” mode but it used in the “prediction” mode. This leads to a quicker and more stable convergence of the estimation algorithm.

Equation (12) indicates that \(\omega_3\) is a constant weight, \(\omega_1\) presents an indirect dependence on the machine speed for the sake of \(f(Q)\) and \(\omega_2\) exhibits a direct dependence on the motor speed then \(\omega_1, \omega_2\) are updated by the back propagation (BP) algorithm.

The final recursive adaption law for the estimated weights is the following, retrieved on the basis of a BP rule
\[
\omega(k+1) = \omega(k) + \eta e(k) U(k)
\]  
(13)

Where \(\eta\) is a positive constant and \(e(k), U(k)\) are defined as follow:
\[
e(k) = \begin{bmatrix}
\psi_{rd}(k) - \psi_{rd}(k-1) \\
\psi_{rq}(k) - \psi_{rq}(k-1)
\end{bmatrix}
\]  
(14)

\[
U(k) = \begin{bmatrix}
\psi_{rd}(k) \\
\psi_{rq}(k)
\end{bmatrix}
\]  

After updating the weights of the neural network at each sample time, the value of speed obtain using Equation (12) and the weight \(\omega_2\).

5- Simulation results

In the last section, the NN MRAS speed observer was designed considering the end effect for LIM. In this section, the proposed method is simulated. This method is compared with the case that the reference model is not updated (standard MRAS method). In order to carry out simulation of the proposed method, we’ll use the motor which its characteristics have been given in Table 1 (Shiri and Shoulaie, 2012).
Table 1. Parameters of slim

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_x (\Omega)$</td>
<td>0.0488</td>
<td>$M (kg)$</td>
<td>29.34</td>
</tr>
<tr>
<td>$R_y (\Omega)$</td>
<td>0.802</td>
<td>$l (m)$</td>
<td>0.412</td>
</tr>
<tr>
<td>$L_{kx} (H)$</td>
<td>0.0014</td>
<td>$\tau (m)$</td>
<td>0.102</td>
</tr>
<tr>
<td>$L_{ly} (H)$</td>
<td>0</td>
<td>$n_p$</td>
<td>4</td>
</tr>
<tr>
<td>$L_{m} (H)$</td>
<td>0.003</td>
<td>$f (Hz)$</td>
<td>146.5</td>
</tr>
</tbody>
</table>

Simulations have been carried out in two stages: the first stage without updating the reference model (standard MRAS) and the second step is performed by updating it. All simulations have been done by MATLAB which sampling frequency of the control system, drive and observer is 10 kHz. In this simulation the drive has been given a speed reference 12m/s at no load.

Fig. 6 shows the diagram of estimated speed and the measured speed. This figure corresponds to the condition that the reference model is not updated. The initial fluctuations are related to the distance of the estimated coefficients from real coefficients. These fluctuations are impossible utilization of the estimated speed in the feedback loop and cause instability of the drive system.

Figure 7. Estimated and measured secondary flux with the standard MRAS method
(Solid line: measured, Dash line: estimated)

Figs. 8 and 9 show the simulation of the second method for the speed and flux. As these figures indicate, using this method we have achieved more accurate estimation of the linear speed.

Figure 8. Estimated and measured linear speed with updating of the reference model

Estimated and measured flux is shown in Fig. 7 by standard MRAS method. This figure shows that the estimated flux and the actual flux has a little difference at the start time, while the difference between the actual and estimated speed is high.

Figure 9. Estimated and measured secondary flux with updating reference model (Dash-dotted line: measured, Dash line: estimated)
In order to ensure performance of drive system at low speeds, linear speed varies from 12 m/s to 4 m/s and it reduces to one-third of its value at t=0.06 (sec). Figure 10 shows estimated and measured speed during this simulation.

Figure 10. Estimated and measured linear speed during operation at low speed with updating of the reference model (Dash-dotted line: measured, Dash line: estimated)

Fig. 11 shows estimation error at the moment of speed change t =0.06 (sec), that it is close to zero in the steady state and it reaches maximum up to 4 m/s at the moment of speed change.

Figure 11. The difference between measured and estimated speed during speed change

To ensure the ability of the observer performance, motor has been made to work for 25 seconds at zero speed with no load. Fig. 12 shows estimated speed and the actual speed of motor during the simulation. This figure clearly shows the ability of the observer’s performance at zero speed. It also shows that the measured speed of motor is exactly zero and the estimated speed of motor is close to zero.

Figure 12. Estimated and measured speed at zero speed (Dash-dotted line: estimated, solid line: measured)

6- Conclusion
In this paper, a new method was proposed based on NN MRAS speed observer. The presented method was simulated for speed control of LIM with FOC method. Using the equations of LIM, the equations of the reference model and adaptive model in the stationary reference frame was presented considering the end-effect. Then the obtained equations showed that unlike the standard MRAS methods, reference model dependent on the motor speed. To solve this problem, a solution was offered in which the equations of the model reference were updated similar to adaptive model. Then to replace the adaptive model with a neural network, the equations were discrete and rewritten so as to be represented by a linear NN. Finally to zero error of outputs in the reference model and adaptive model, BP algorithm was used. The performance of this method was demonstrated by simulations.

7- References
considering attraction force & transverse edge effect. 9th IEEE International. IEEE, 158-163.


