Adaptive backstepping control of linear induction motors using artificial neural network for load estimation

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Article Info

ABSTRACT

Linear induction motors (LIMs) make performing a direct linear motion possible without any mechanical rotary to linear motion transforming parts. Obtaining a precise mathematical model of such type of motors presents a difficulty due to time varying parameters and external load disturbance. This paper proposes an adaptive backstepping controller structure based on lyapunov stability for controlling a LIM position. Which can guarantee the annulment of position tracking error, despite of parameter uncertainties. Parameter update laws are extracted to estimate mover mass, friction coefficient and load force disturbance, which are assumed to be constant parameters; as a result, compensating their undesirable effect on control design. Then, load disturbance estimate is replaced with an artificial neural network (ANN) to reduce the estimation error. The numerical validation has shown better performance compared to the conventional backstepping controller, and proved the robustness of the proposed adaptive controller design against parameter changes.

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1. INTRODUCTION

Linear induction motors (LIMs) are widely used in industry and transportation applications [1], [2]. This type of motors offers the ability to perform a direct linear motion without the need of any mechanical rotary to linear motion transforming parts [3]. The driving principle of the LIM is similar to that of a rotary induction motor (RIM), however, the control characteristics are more complicated: operating conditions such as speed of mover, temperature and rail configuration result variations in LIM parameters [4], [5]. Field oriented control (FOC) is considered as the most used high performance control method for AC motors. Its main idea is to make the control design similar to that in a separately excited DC machine, by decoupling the dynamics of thrust force and rotor flux [6]-[8]. Unfortunately, a good performance of such control can only be achieved by using a precise plant model, which is very difficult, because unlike RIM the model of LIM presents more complexity due to parameter variations. Many researches in modeling LIM dynamics have been done, taking into consideration parameter variations and end effect phenomenon [3], [6], [9]-[11]. However, modeling uncertainties are always present due to undesirable behaviors and load disturbance.

The advancement in nonlinear control field has offered multiple solutions to deal with modeling changes. One of these solutions is backstepping control. This nonlinear control technique has been widely

applied in controlling LIMs [12]-[16]. The design idea is the decomposition of a complex high order control structure into low order steps. Where in every step a new reference is chosen to stabilize the previous one using "virtual control" variables, until reaching a real control input that garentees the stability of the global structure using lyapunov function. Moreover, using the adaptive version of backstepping control insures attaining the global structure's stability despite of parameter variations, thanks to parameter update laws [12]-[16]. The obtained results in previous works have shown better performance comparing to FOC when facing modeling uncertainties [16]. However, the linearity assumptions in the design may not always be true. The load disturbance for example is neither linear nor constant in most cases.

Parallel to fast development in robust and adaptive control techniques, artificial neural networks (ANNs) have been widely applied to system identification, and identification based control. They are known to be universal approximators. ANN based controllers have been proposed for a variety of control applications that can provide closed-loop stability [17]-[21]. In this paper, an adaptive backstepping control structure is proposed in order to track a desired position trajectory of a LIM, under the assumption of unknown moving part mass, friction coefficient and load disturbance. Then, an ANN estimation structure is introduced to replace the external load disturbance estimate. The paper is organized as follows: section 2 introduces the proposed adaptive backstepping controller design with ANN estimator. Section 3 presents the numerical validation results followed by discussion. Finally, a conclusion is summarized in section 4.

2.   ADAPTIVE BACKSTEPPING CONTROL

The construction principle of a LIM is shown in Figure 1. The primary can be seen as a "cut-open and rolled-flat" RIM primary, and the secondary usually consists of a sheet conductor, with an iron back for the return path of the magnetic flux. For a neglected relative velocity, the LIM primary can be considered as infinite, as a result, the end effects may be ignored [13].
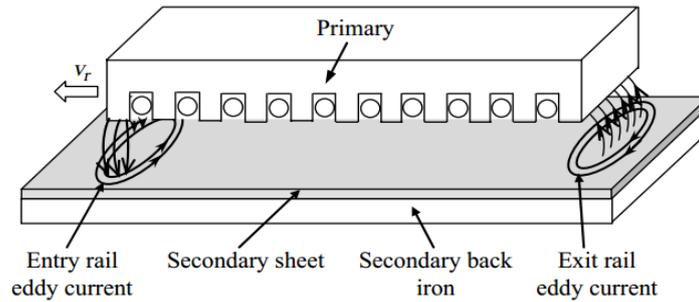

Figure 1. LIM construction

The mathematical model of the LIM in the d-q axis reference frame can be modified from a three phase Y-connected RIM, which gives [12], [13]:

$$\frac{di_{ds}}{dt} = -\frac{1}{\sigma L_s}\left(R_s + \left(\frac{L_m}{L_r}\right)^2 R_r\right).i_{ds} + \frac{\pi}{h}V_e.i_{qs} + \frac{L_m R_r}{\sigma L_s L_r{}^2}.\phi_{dr} + \frac{PL_m\pi}{\sigma L_s L_r h}.\phi_{qr}.v + \frac{1}{\sigma L_s}V_{ds} \tag{1}$$

$$\frac{di_{qs}}{dt} = -\frac{\pi}{h}V_e.i_{ds} - \frac{1}{\sigma L_s}\left(R_s + \left(\frac{L_m}{L_r}\right)^2 R_r\right).i_{qs} - \frac{PL_m\pi}{\sigma L_s L_r h}.\phi_{dr}.v + \frac{L_m R_r}{\sigma L_s L_r{}^2}.\phi_{qr} + \frac{1}{\sigma L_s}V_{ds} \tag{2}$$

$$\frac{d\phi_{dr}}{dt} = \frac{L_m R_r}{L_r}.i_{ds} - \frac{R_r}{L_r}.\phi_{dr} + \frac{\pi}{h}(V_e - P.v).\phi_{qr} \tag{3}$$

$$\frac{d\phi_{qr}}{dt} = \frac{L_m R_r}{L_r}.i_{qs} - \frac{\pi}{h}(V_e - P.v).\phi_{dr} - \frac{R_r}{L_r}\phi_{qr} \tag{4}$$

$$F_e = K_f(\phi_{dr}i_{qs} - \phi_{qr}i_{ds}) = M\frac{dv}{dt} + f_c.v + F_L \tag{5}$$

where R_s is the stator resistance, R_r is the rotor resistance, L_s is the stator inductance, L_r is the rotor inductance, L_m is the mutual inductance, P is the pole pairs number, h is the pole pitch, $\sigma = 1 - (L_m^2/L_s L_r)$ is the leakage coefficient, V_e is the linear synchronous velocity, v is the linear mover velocity, i_{ds} is the

d-axis stator current, i_{qs} is the q-axis stator current, ϕ_{dr} the d-axis rotor flux, ϕ_{qr} is the q-axis rotor flux, V_{ds} is the d-axis stator voltage, V_{qs} is the q-axis stator voltage, $K_f = 3P\pi L_m/(2L_r h)$ is the force constant, F_e is the applied electromagnetic force, F_L is the load force disturbance, M is the total mover mass and f_c is the friction coefficient. The basic backstepping design idea is the decomposition of a high order nonlinear system into small first order subsystems, using "virtual control" variables [22]. Where every control variable is chosen in a way that can stabilize the previous subsystem, introducing a corresponding error that can be compensated by selecting a convenient control input via lyapunov stability [7], [13], [14], [23].

2.1. Controller design

Introducing the position tracking error:

$$e_1 = d_{ref} - d \tag{10}$$

its dynamic gives.

$$\dot{e}_1 = \dot{d}_{ref} - \dot{d} = \dot{d}_{ref} - v \tag{11}$$

We introduce the first lyapunov function candidate,

$$V_1 = \frac{1}{2}e_1^2 \tag{12}$$

it's time derivate gives,

$$\dot{V}_1 = e_1\dot{e}_1 = e_1(\dot{d}_{ref} - v) \tag{13}$$

if the first stabilising function is chosen as,

$$v_{ref} = k_1 e_1 + \dot{d}_{ref} \tag{14}$$

where k_1 is a positive constant, the dynamic of V_1 gives,

$$\dot{V}_1 = -k_1 e_1^2 \leq 0 \tag{15}$$

which insures the stabilisation of the closed-loop control.

However, v is a "virtual control" input, a new tracking error is defined in (16).

$$e_2 = v_{ref} - v \tag{16}$$

To ensure the elimination of the position tracking error despite of modeling inaccuracy and load disturbance, an integral action is introduced to the velocity reference as follows [15]:

$$v_{ref} = k_1 e_1 + \dot{d}_{ref} + k_1' e_1' \tag{17}$$

where $e_1' = \int e_1(t)dt$ and k_1' is a positive design constant.

Deriving the velocity tracking error to time gives,

$$\begin{aligned}
\dot{e}_2 &= \dot{v}_{ref} - \dot{v} \\
&= \ddot{d}_{ref} + k_1\left(\dot{d}_{ref} - v\right) + k'_1 e_1 - \frac{F_e}{M} + \frac{f_c}{M}v + \frac{F_L}{M}
\end{aligned} \tag{18}$$

so the dynamic of e_1 can be rewritten as,

$$\dot{e}_1 = -k_1 e_1 + k_1' e_1' + e_2 \tag{19}$$

define a new lyapunov function,

$$V_2 = \frac{1}{2}e_1^2 + \frac{1}{2}e_2^2 + \frac{k_1'}{2}e_1'^2 \tag{20}$$

deriving to time and using (18) and (19) results,

$$\dot{V}_2 = -k_1 e_1^2 - k_2 e_2^2 + e_2[e_1(1 - k_1^2 + k_1') + k_1'k_1e_1' + e_2(k_1 + k_2) + \ddot{d}_{ref} - \frac{F_e}{M} + D.v + L] \quad (21)$$

where k_2 is a positive constant, $D = f_c / M$ is the normalized friction coefficient and $L = F_L / M$ is the normalized Load disturbance. Now, the force control input F_{e_ref} that guarantees achieving the desired position trajectory is to be chosen. If we choose (22),

$$F_{e\_ref} = M[e_1(1 - k_1^2 + k_1') + k_1'k_1e_1' + e_2(k_1 + k_2) + \ddot{d}_{ref} + D.v + L] \quad (22)$$

we get,

$$\dot{V}_2 = -k_1 e_1^2 - k_2 e_2^2 \le 0 \quad (23)$$

which ensures the stabilization of the closed-loop control.

However, M, D and L are considered as unknown parameters, so their estimates $\hat{M}$, $\hat{D}$ and $\hat{L}$ are used instead, (23) becomes (24).

$$\hat{F}_{e\_ref} = \hat{M}[e_1(1 - k_1^2 + k_1') + k_1'k_1e_1' + e_2(k_1 + k_2) + \ddot{d}_{ref} + \hat{D}.v + \hat{L}] \quad (24)$$

Next step is to extract estimation update laws. Define the following parameter estimation errors.

$$\widetilde{M} = M - \hat{M} \quad (25)$$

$$\widetilde{D} = D - \hat{D} \quad (26)$$

$$\tilde{L} = L - \hat{L} \quad (27)$$

Using these definitions and the applied force control (24), the dynamic of e_2 in (18) gives,

$$\dot{e}_2 = -e_1 - k_2 e_2 + \hat{D}.v + \hat{L} + \frac{\widetilde{M}}{M}\beta \quad (28)$$

where $\beta = [e_1(1 - k_1^2 + k_1') + k_1'k_1e_1' + e_2(k_1 + k_2) + \ddot{d}_{ref} + \hat{D}.v + \hat{L}]$.

Finally, the system's final lyapunov function that contains all error signals is build, in order to extract update laws of the estimated parameters,

$$V_3 = \frac{1}{2}e_1^2 + \frac{1}{2}e_2^2 + \frac{k_1'}{2}e_1'^2 + \frac{1}{2\delta_1 M}\widetilde{M}^2 + \frac{1}{2\delta_2}\widetilde{D}^2 + \frac{1}{2\delta_3}\tilde{L}^2 \quad (29)$$

where δ_1, δ_2 and δ_3 are positive constants.

Assuming M, D and L are constant parameters, It can be written,

$$\dot{\widetilde{M}} = -\dot{\hat{M}} \quad (30)$$

$$\dot{\widetilde{D}} = -\dot{\hat{D}} \quad (31)$$

$$\dot{\tilde{L}} = -\dot{\hat{L}} \quad (32)$$

Using (30), (31), (32) and the error dynamics in (19) and (28) we calculate the time derivative of (29). After substitution and simplification, the result is:

$$\dot{V}_3 = -k_1 e_1^2 - k_2 e_2^2 + \frac{\widetilde{M}}{M}\left(e_2\beta - \frac{1}{\delta_1}\dot{\hat{M}}\right) + \widetilde{D}\left(e_2v - \frac{1}{\delta_2}\dot{\hat{D}}\right) + \tilde{L}\left(e_2 - \frac{1}{\delta_3}\dot{\hat{L}}\right) \quad (33)$$

The chosen update laws to render the system's global lyapunov function negative are as follows:

$$\dot{\hat{M}} = \delta_1 e_2 \beta \tag{34}$$

$$\dot{\hat{D}} = \delta_2 e_2 v \tag{35}$$

$$\dot{\hat{L}} = \delta_3 e_2 \tag{36}$$

The resulting lyapunov function dynamic gives,

$$\dot{V}_3 = -k_1 e_1^2 - k_2 e_2^2 \leq 0 \tag{37}$$

which guarantees stabilising of the global system and achieving desired position trajectory, despite the presence of parameter uncertainties and load disturbance.

2.2. ANN load disturbance estimator

From (36), the load disturbance estimate can be written as (38).

$$\hat{L} = \delta_3 \int e_2 \, d\,t \tag{38}$$

In the next approach, we will replace the load disturbance estimate with an ANN structure in order to reduce the load disturbance estimation error. We have chosen an ANN structure with single input e_2 and single output $\hat{L}_{NN}$. The chosen ANN contains three layers: the input layer has one neuron and no activation function, the hidden layer consists of 5 neurons with tangent-sigmoid activation function, and the output layer has one neuron with purelin activation function. The selected ANN was trained off-line using previous controller results.

The basic feed-forward three-layer neural network model is given as [24], [25].

$$y_k(x, w) = f\left(\sum_{j=1}^{M} w_{k,j} g\left(\sum_{i=1}^{N} w_{j,i} x_i + b_i\right) + b_j\right) \tag{39}$$

where $y_1, \ldots, y_k$ are output variables, f is the output layer activation function, $x_1, \ldots, x_N$ are input variables, $w_{k,j}$ and b_j are respectively hidden to output layer weights and bias, g is the hidden layer activation function, $w_{i,j}$ and b_i are respectively input to hidden layer weights and bias.

Applying the the neural network form in (39) to the load disturbance estimate in (38), our ANN structure can be written as (40).

$$\hat{L}_{NN} = f\left(\sum_{j=1}^{5} w_{2,j} g\left(w_{1,i} e_2 + b_i\right) + b_j\right) \tag{40}$$

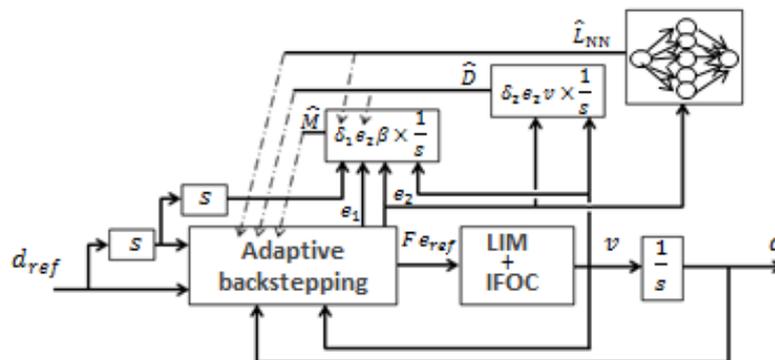The final adaptive backstepping controller design with ANN estimate is summarized in diagram of Figure 2.

Figure 2. Adaptive backstepping control with ANN estimator

3. RESULTS AND DISCUSSION

In the following, we run numerical simulation in which the performance of the adaptive backstepping controller under different operating conditions is tested (Mass, friction and load disturbance variations). For that purpose, we run numerical simulation for the following cases:

− Case (1): variation of mass equals to 3×M. The results are shown in Figure 3.
− Case (2): variation of friction coefficient equals to 10×D. The results are shown in Figure 4.
− Case (3): a force disturbance equals to 20N is injected between t=5s and t=7s. The results are shown in Figure 5.

The obtained results are compared to conventional backstepping controller performance. The machine parameters used for numerical validation are presented in Table 1.

Table 1. LIM parameters

Parameter	Value
R_s	3.4 (Ω)
R_r	1.95 (Ω)
L_s	0.1078 (H)
Lr	0.1078 (H)
L_m	0.1042 (H)
P	2
M M	5.47 (Kg)
f_c	2.36 (Nm.s/rd)

The chosen trajectory is a periodic step of ±0.1m and the controller's parameters and update laws are selected as: $k_1 = 10$, $k_1' = 0.02$, $k_2 = 120$, $\delta_1 = 0.001$, $\delta_2 = 0.01$, $\delta3 = 500$.

3.1. Mover mass variation

In the first case, the results show that the adaptive backstepping control is insensitive against mover mass change. Even when the mass value rose to triple, the controller is always insensitive and can track the desired position trajectory successfuly with fast response time and no overshoot Figure 3a. In the other hand, the conventional controller has suffered a tracking response overshoot, before it could achieve the reference. As a result, there was a delay in response time. The electromagnetic force, stator current and rotor fluxes are shown in Figures 3(b)-(d) consecutively.
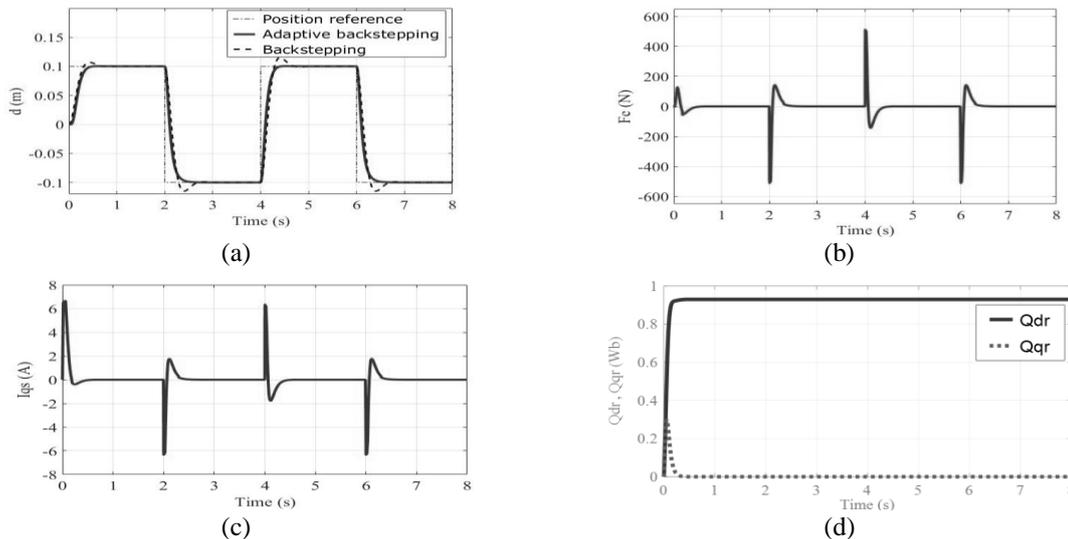

Figure 3. Adaptive backstepping control of LIM position with 3×M, (a) position tracking response, (b) applied electromagnetic force, (c) stator current Iqs, and (d) rotor fluxes

3.2. Friction coefficient variation

In case 2, where the friction coefficient value has risen by 10 times, both controllers had nearly no noticeable effect. The response time is fast and there is no overshooting as shown in Figure 4(a). That shows that backsteppnig control is insensitive against friction variations too. The electromagnetic force, stator

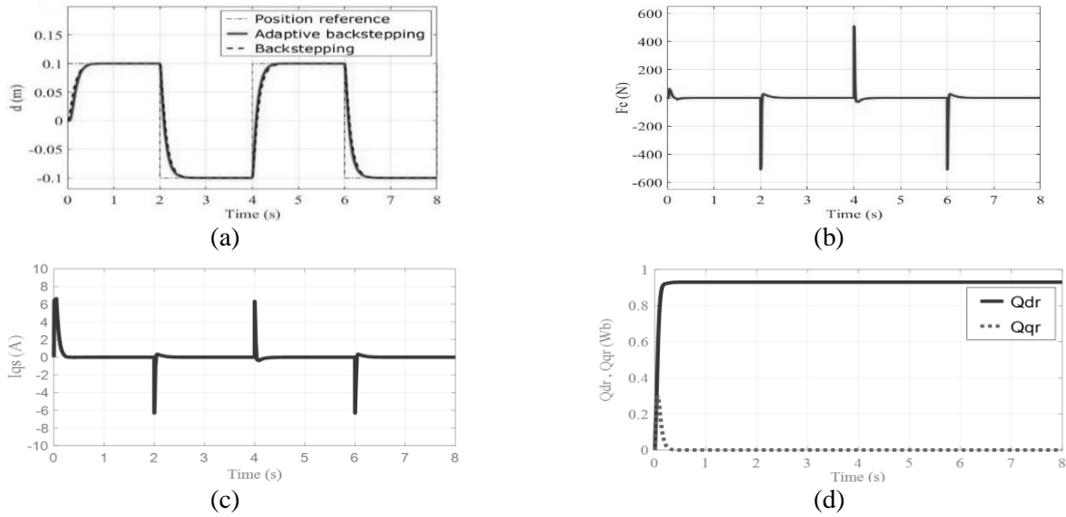current and rotor fluxes are shown in Figures 4(b)-(d) consecutively

(a)   (b)

(c)   (d)

Figure 4. Adaptive backstepping control of LIM position with 10×D: (a) position tracking response, (b) applied electromagnetic force, (c) stator current Iqs, and (d) rotor fluxes

3.3. Load disturbance

In case 3, viewing Figure 5 we can see the effect of load disturbance on the conventional controller, a non-null static error was generated causing a failure in following the position trajectory as seen in Figure 5(a). In the other hand, the adaptive backstepping controller was able to compensate the effect of load disturbance in fast time. In addition, using the ANN estimate has made the controller insensitive against load disturbance, making the position tracking successful with no noticeable effect. The applied electromagnetic force, stator current and rotor fluxes are shown in Figures 5(b)-(d) consecutively.

(a)   (b)

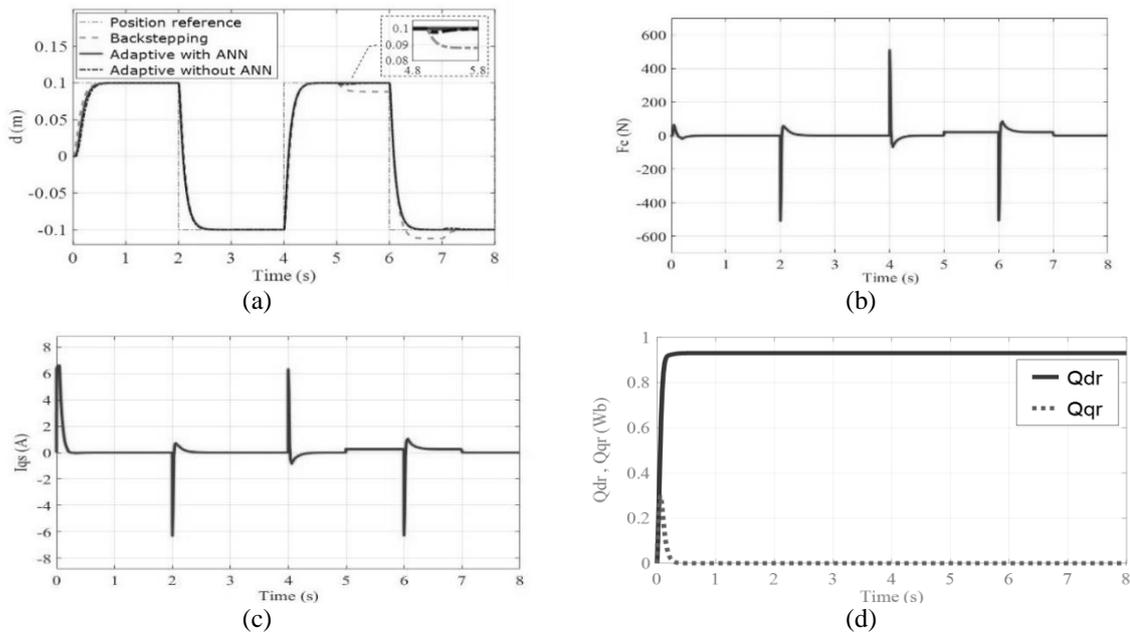(c)   (d)

Figure 5. Adaptive backstepping control of LIM position with applied load disturbance equals to 20N; (a) position tracking response, (b) applied electromagnetic force, (c) stator current Iqs, and (d) rotor fluxes

The previous simulation results show great performance and prove the robustness of the proposed adaptive backstepping control structure, thanks to parameter update lows using lyapunov function. Which insures the global system's stability despite of parameter uncertainties. The parameter estimates are presented in Figure 6. We can observe that the estimation errors are null for mover mass in Figure 6(a) and friction coefficient in Figure 6(b). For the load disturbance estimates in Figure 6(c), we can see that the estimation error was considerable and can't be neglected for the structure with no use of ANN. This problem is the main reason we proposed the replacement of the load disturbance estimate with an ANN estimator. This structure has reduced the estimation error. It can be noticed that load disturbance estimation converges to the real value, with better and more acceptable response time and error range using ANN, allowing the controller to successfully track the desired trajectory. The amelioration was noticeable on the position tracking where the controller became insensitive, and the disturbance had no effect on position tracking.
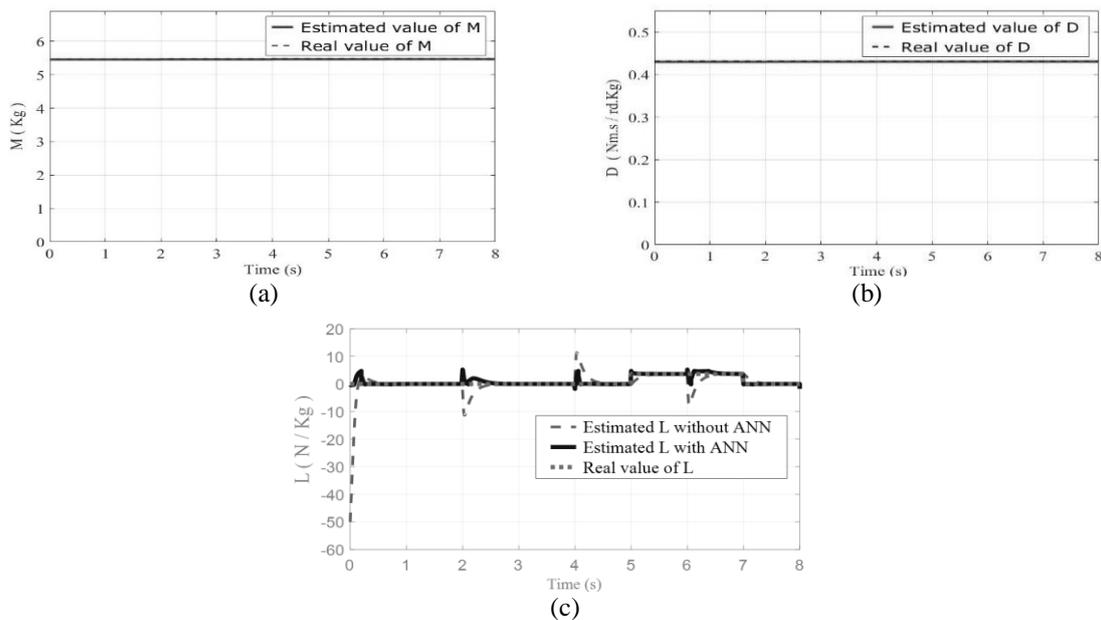

Figure 6. Parameters estimates: (a) mover mass, (b) friction coefficient, and (c) load force disturbance

4. CONCLUSION

This paper has proposed an adaptive backstepping control structure using artificial neural network for load disturbance estimation, to control a LIM position. The controller's structure was designed and parameter update laws were extracted, to track a desired position trajectory, assuming that some LIM parameters are uknown. The robustness of the proposed controller was checked under different operating conditions. The obtained simulation results have shown a great position tracking performance compared to conventional backstepping. And they have proven it's insensitivity against parameter variations, and it's ability to compensate load disturbance effect without overshoot, thanks to parameter update laws and ANN estimation structure. Finally, the research directions of this paper can be extended in the future, to the use of ANN backstepping controller in tracking the speed of LIM. Which means considering the end effect phenomenon when modeling LIM.

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