A neural network based speed control of a linear induction motor drive

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Abstract— **In this paper, a general regression neural network (GRNN) based controller is used to control the speed and thrust output of the linear induction motor drive. The field orientation principle is used to asymptotically decouple the motor speed from the secondary flux. The idea of model predictive control technique is used for the training of the proposed controller. The motivation for using this control strategy for training the GRNN based controller is to reduce the effect of the uncertainty due to motor parameters variation and load disturbance. This newly developed design strategy combines the advantage of the neural networks and MPC control techniques to provide robust performance and leads to a flexible controller with simple structure that is easy to implement. Digital simulations have been carried out to validate the effectiveness of the proposed scheme. The results of the proposed controller are compared with the corresponding one using the traditional PI controller. The results show that, the proposed technique has the ability to control successfully the speed and thrust of the linear induction drive in face of the motor parameters variation or load force disturbance.**

Keywords- Linear induction motor – Field orientation – Electrical elevator - model predictive control.

1. INTRODUCTION

Due to its several advantages such as high starting thrust, alleviation of gears between motor and the motion devices, simple mechanical construction, no backlash and less friction, and suitability for low speed and high speed applications [1-4]. Linear induction motor (LIM) has been widely used in a variety of applications like as transportation, conveyor systems, actuators, material handling, pumping of liquid metal, sliding door closers, curtain pullers, robot base movers, office automation, drop towers, elevators,..etc.

LIM and traditional rotary induction motor have similar driving principles. However, the control characteristics of the LIM are more complicated. This is attributed to the time varying motor parameters as a result of change in operating conditions such as mover speed, temperature, and rail configuration. Moreover, there are uncertainties existed in practical applications of the LIM [5-7] which usually composed of unpredictable plant parameter variations, external load disturbance, and un-modeled and nonlinear dynamics. Furthermore, since the operation of LIM involves two contact bodies, friction force is inevitably among the forces of motion and results in steady state error, limit cycle and low bandwidth. In addition, the friction characteristics may be easily varied due to the change of normal forces in contact, temperature and humidity. Therefore, the LIM drive system must provide high tracking performance, and high dynamic stiffness to overcome the above difficulties.

Because of the rapid improvements in power electronic devices and microelectronics, the field oriented control technique has made possible the high performance applications of induction motor drives [9-10]. Therefore, it can be applied to the LIM by aligning the d-axis of the primary current with the secondary flux linkage. However, the sensitivity to parameters variation is considered the main drawback of this method.

In the past few years, modern control techniques have been used to control the speed and/or position of the induction motor drives: direct torque control (DTC) technique [11], sliding mode control method [12-13], linear quadratic Gaussian (LQG) method [14], also, Intelligent methods such as neural, fuzzy and genetic algorithm have been employed for this purpose [15-17]. However, an induction motor is a highly coupled, nonlinear dynamic plant. It is difficult to obtain good performance for an entire speed range and transient states using previous methods.

On the other hand, MPC appears to be an efficient strategy to control many applications in industry, it has many advantages such as very fast response, robustness against load disturbance and parameters uncertainty, also, it can efficiently control a great variety of processes, including systems with long delay times, non-minimum phase systems, unstable systems, multivariable systems, constrained system[18-19].

There has been considerable interest in the past few years in exploring the applications of neural network NN to deal with nonlinearities and uncertainties of the control systems [16].

Because the NN can be used for a universal approximator like fuzzy and neural systems [23], it has been introduced as a possible solution to the real multivariate interpolation problem. However, there must inevitably be a reconstruction error if the structure of the NN (the number of activation functions in the hidden layer) is not infinitely rich. These errors are introduced into the closed-loop system and deteriorate the stability. To compensate for the reconstruction error, [24].

In this paper, a GRNN speed control of the field oriented LIM drive has been presented. The field orientation principle is used to decouple the mover speed from the secondary flux amplitude.

The idea of MPC control technique is being used for training the proposed GRNN based controller. The motivation for using this control technique for training the GRNN is to take large modeling uncertainties into account, and minimize the effects of load disturbances. To achieve the desired level of robust performance, the training data is obtained by designing MPC controller for various operating conditions and applying them to the restructured power system in the presence of plant parameter changes and load disturbance. The proposed controller is then reconstructed using the learning capability of neural networks. Moreover, the proposed control strategy has simple structure, Thus, its implementation is fairly easy and can be used in the real world system. The proposed control strategy is tested under the motor parameters variation and load disturbance. A comparison has been made between the response of the GRNN, MPC , and the traditional PI controllers. Simulation results proved that the proposed controller can be applied successfully to control the speed of the LIM drive and provide the best performance.

The paper is organized as follows: Section 2 presents the dynamic model of the linear induction motor. Indirect field oriented technique is described in section 3. General consideration about MPC and its cost function are presented in section 4. The methodology of the GRNN is presented in section 5.The implementation scheme of the LIM drive together with the GRNN controller is described in section 6. Simulation results and general remarks are presented in section 7. Finally, the conclusions and future work are given in section 8.

2. LIM DYNAMIC MODEL

The electrical dynamic model of the LIM is modified from the traditional model of a three phase, Y-connected induction motor in $\alpha - \beta$ stationary frame and can be described by the following differential equations [20]:

$$p\, i_{\propto s} = -\left(\frac{R_s}{\sigma L_s} + \frac{1-\sigma}{\sigma T_r}\right) i_{\alpha s} + \frac{L_m}{\sigma L_s L_r T_r}\lambda_{\alpha r} + \frac{n_p L_m \pi}{\sigma L_s L_r h} v \lambda_{\beta s} + \frac{1}{\sigma L_s} V_{\alpha s} \quad (1)$$

$$p\, i_{\beta s} = -\left(\frac{R_s}{\sigma L_s} + \frac{1-\sigma}{\sigma T_r}\right) i_{\beta s} + \frac{L_m}{\sigma L_s L_r T_r}\lambda_{\beta r} - \frac{n_p L_m \pi}{\sigma L_s L_r h} v \lambda_{\alpha s} + \frac{1}{\sigma L_s} V_{\beta s} \quad (2)$$

$$p\, \lambda_{\alpha r} = \frac{L_m}{T_r} i_{\alpha s} - \frac{1}{T_r}\lambda_{\alpha r} - \frac{n_p \pi}{h} v \lambda_{\beta r} \quad (3)$$

$$p\, \lambda_{\beta r} = \frac{L_m}{T_r} i_{\beta s} - \frac{1}{T_r}\lambda_{\beta r} + \frac{n_p \pi}{h} v \lambda_{\alpha r} \quad (4)$$

$$pv = \frac{1}{M} F_e - \frac{D}{M} v - \frac{1}{M} F_L \quad (5)$$

Where, $T_r = \frac{L_r}{R_r}$, and $\sigma = 1 - \frac{L_m^2}{L_s L_r}$

T_r : Secondary time constant,
L_r : Secondary inductance per phase,
R_r : Secondary resistance per phase,
L_m : Magnetizing inductance per phase,
R_s : Primary winding resistance per phase,
L_s : Primary inductance per phase
v : Mover linear velocity,
$\lambda_{\alpha r}, \lambda_{\beta r}$: $\alpha - \beta$ secondary flux components,
$i_{\alpha s}, i_{\beta s}$: $\alpha - \beta$ primary current components,
$V_{\alpha s}, V_{\beta s}$: $\alpha - \beta$ primary voltage components,
σ : Leakage coefficient,
h : Pole pitch,
n_p : Number of pole pairs.
p : Differential operator.
F_e : electromagnetic force,
F_L : external force disturbance,
M : total mass of the moving element,
D : viscous friction and iron-loss coefficient

3. INDIRECT FIELD ORIENTED LIM

In the field oriented control method, the dynamics of the highly coupled nonlinear structure of the induction machine becomes linearized and decoupled. The decoupled relationship is obtained by proper selection of state coordinates, under the hypothesis that the rotor flux is kept constant [17]. Therefore, the rotor speed is only asymptotically decoupled from the rotor flux, and is linearly related to the torque current only after the rotor flux becomes in the steady state.
The flux model of the LIM can be described in the d-q synchronous frame as:

$$p\lambda_{dr} = \frac{L_m}{T_r} i_{ds} - \frac{1}{T_r}\lambda_{dr} + \left(\frac{\pi}{h} v_e - \frac{n_p \pi}{h} v\right)\lambda_{qr} \quad (\mathbf{6})$$

$$p\lambda_{qr} = \frac{L_m}{T_r} i_{qs} - \frac{1}{T_r}\lambda_{qr} - \left(\frac{\pi}{h} v_e - \frac{n_p \pi}{h} v\right)\lambda_{dr} \quad (7)$$

Where:

$\lambda_{dr}, \lambda_{qr}$: $d - q$ secondary flux components,
i_{ds}, i_{qs} : $d - q$ primary current components,
$v_e = 2hf$: synchronous linear velocity ,
f :supply frequency.

In an ideally decoupled induction motor, the secondary flux linkage axis is forced to be aligned with the d-axis, and the field orientation conditions can be applied. It follows that:

$$\lambda_{qr} = 0 \quad , \quad \text{and} \quad p\lambda_{dr} = p\lambda_{qr} = 0 \quad (8)$$

Using (8), the desired secondary flux linkage in terms of i_{ds} can be found from (6) as

$$\lambda_{dr} = L_m i_{ds} \quad (9)$$

Moreover, (7) can be combined with (8) and (9) to give the feedforward slip velocity signal as follows:

$$v_{sl} = \frac{\pi}{h} v_e - \frac{n_p \pi}{h} v = \frac{i_{qs}}{T_r\, i_{ds}} \quad (10)$$

The electromagnetic force can be described in the d-q synchronous frame as [17]:

$$F_e = k_f \left(\lambda_{dr} i_{qs} - \lambda_{qr} i_{ds} \right) \quad (11)$$

Where k_f is the force constant which is equal to:

$$k_f = \frac{3 n_p L_m \pi}{2 L_r h}$$

With the implementation of the field oriented control, (11) can be rewritten using (8) and (9) as:

$$F_e = K_F i_{qs} \quad (12)$$

Where

$$K_F = k_f L_m i_{ds}$$

If the d-axis primary current (flux current component) is kept constant at the rated value, therefore the electromagnetic force is directly proportional to the q-axis current; which can be realized via closed loop control. In this case, if the q-axis current (load current component) is rapidly changed in response to the load variation, this will be followed by a rapid change in the motor developed force and the LIM will exhibit a high dynamic performance.

4. MODEL PREDICTIVE CONTROL

Due to it is considered as simple and effective control technique. MPC has proved to efficiently control a wide range of applications in industry such as : chemical process, petrol industry, electromechanical systems and many other applications. The MPC scheme is based on an explicit use of a prediction model of the system response to obtain the control actions by minimizing an objective function. Optimization objectives include minimization of the difference between the predicted and reference response, and the control effort subjected to prescribed constraints. The effectiveness of MPC is demonstrated to be equivalent to the optimal control. It displays its main strength in its computational expediency, real-time applications, intrinsic compensation for time delays, treatment of constraints, and potential for future extensions of the methodology. At each control interval, the first input in the optimal sequence is sent into the plant, and the entire calculation is repeated at subsequent control intervals. The purpose of taking new measurements at each time step is to compensate for unmeasured disturbances and model inaccuracy, both of which cause the system output to be different from the one predicted by the model[18-19].

Figure 1 shows a simple structure of the MPC controller. An internal model is used to predict the future plant outputs based on the past and current values of the inputs and outputs and on the proposed optimal future control actions. the prediction has two main components : The free response which being expected behavior of the output assuming zero future control actions, and the forced response which being the additional component of the output response due to the candidate set of future controls. For linear systems, the total prediction can be calculated by summing both of free and forced responses, reference trajectory signal is the target values the output should attain. The optimizer is used to calculate the best set of future control action by minimizing the cost function J, the optimization is subject to constraints on both manipulated and controlled variables [21,22].

The general object is to tighten the future output error to zero, with minimum input effort. The cost function to be minimized is generally a weighted sum of square predicted errors and square future control values, e.g. in the Generalized Predictive Control (GPC) :

$$J(N1, N2, N3) = \sum_{j=N_1}^{N_2} \beta(j)\, [\hat{y}(k+j|k) - w(k+j)]^2 + \sum_{j=1}^{N_u} \lambda(j) [u(k+j-1)]^2 \quad (13)$$

Where N_1 , N_2 are the lower and upper prediction horizons over the output, N_u is the control horizon, $\beta(j), \lambda(j)$ are weighting factors. The control horizon permits to decrease the number of calculated future control according to the relation: $\Delta u(k+j) = 0$ for $j \geq N_u$.

$w(k+j)$ represents the reference trajectory over the future horizon N.

Constraints over the control signal, the outputs and the control signal changing can be added to the cost function:

$$\begin{aligned} u_{min} &\leq u(k) \leq u_{max} \\ \Delta u_{min} &\leq \Delta u(k) \leq \Delta u_{max} \\ y_{min} &\leq y(k) \leq y_{max} \end{aligned} \quad (14)$$

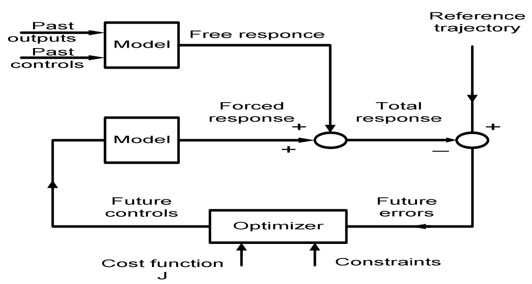


Fig. 1 A simple structure of the MPC controller.

Solution of (13) gives the optimal sequence of control signal over the horizon N while respecting the given constraints of (14).
Model Predictive Control have many advantages, in particularly it can pilot a big variety of process, being simple to apply in the case of multivariable system, can compensate the effect of pure delay by the prediction, inducing the anticipate effect in closed loop, being a simple technique of control to be applied and also offer optimal solution while respecting the given constraints. On the other hand, this type of restructure required the knowledge of model for the system, and in the present of constraints it becomes a relatively more complex regulator than the PID for example, and it takes more time for on-line calculations

5. ADAPTIVE PREDICTION MODEL BY GRNN

The generalized regression neural network (GRNN) [26] is a feed-forward neural network based on non-linear regression theory consisting of four layers: the input layer, the pattern layer, the summation layer, and the output layer (see Fig. 2). Regression can be thought of as the least-mean-squares estimation of the value of a variable based on available data. The GRNN is principally a normalized Radial Basis Function RBF network for which a hidden unit is centered at every training sample and a special linear layer. The RBF units of the GRNN architecture are generally characterized by the Gaussian kernels. The hidden layer to output layer weights are just the target values, so that the output is simply a weighted average of the target values of training cases close to the given input case. The first layer is just like of an RBF network with as many neurons as there are input/target vectors. Choosing the spread parameters σ of the radial basis function determines the width of an area in the input space, to which each basis function responds [27]. Adaptation is important to fine-tune the predicted performance of LIM drive. The applied GRNN predictor has major dynamic features which are:- fast training, modeling of non-linear functions, good performance in noisy environments given enough data or even in a changing environment data. The targets of each of the nodes are constantly updated, which can improve if there is any error during the training phase. It also helps to adapt the model accordingly to environmental changes. The idea is to merge the existing target with the feed in training target within a certain ratio. Finally, the gradient descent back-error propagation learning method based on the prediction error is continuously applied to further fine-tune the GRNN performance. The gradient of the prediction error of the GRNN can be computed by using partial differentiation method, and updated as in [25,26]. Training of a GRNN is performed in one pass of the training data through the network. The training of the GRNN is completed after presentation of each input-output vector pair from the training set to the GRNN input layer only once; that is, both the centers of the radial basis functions of the pattern units and the weights in connections of the pattern units and the processing units in the summation layer are assigned simultaneously. The training of the pattern units is unsupervised, but employs a special clustering algorithm, which makes it unnecessary to define the number of pattern units in advance. Instead, it is the radius of the clusters that needs to be specified before the training starts. The GRNN computes the predicted values "on the fly" from the training values, using the basis functions defined below[30]
The outputs of the hidden layer units are of the form

$$\varphi_k(X) = \exp\left[-\frac{(X-V_k^X)^T.(X-V_k^X)}{2\sigma^2}\right] \quad (15)$$

When V_k^X are the corresponding clusters for the inputs and V_k^y are the corresponding clusters for the outputs obtained by applying a clustering technique of the input/output data that produces K cluster centers [29].
Where:

$$V_k^y = \sum\nolimits_{y(p)\in \text{clusters } k} y(p) \quad (16)$$

While N_k is the number of input data in the cluster center k, and

$$d(X, V_k^x) = (X - V_k^x)^T(X - V_k^x) \quad (17)$$

with

$$V_k^X = \sum\nolimits_{X(p)\in \text{clusters } k} X(p) \quad (18)$$

The outputs of the hidden layer nodes are multiplied with appropriate interconnection weights to produce the output of the GRNN. The weight for the hidden node k (i.e w_k) is equal to :

$$w_k = \frac{V_k^x}{\sum_{k=1}^{K} N_k \exp\left[-\frac{d(X,V_k^x)^2}{2\sigma^2}\right]} \quad (19)$$

The selection of an adequate set of training examples is very important in order to achieve good generalization properties. The set of all available data is separated in two disjoint sets: training set and test set. The test set is not involved in the learning phase of the networks and it is used to evaluate the performances of the models [31].
The configuration of the neural network model is determined by the nature of the problem to be solved. The dimension of the input vector used defines the number of inputs neurons.

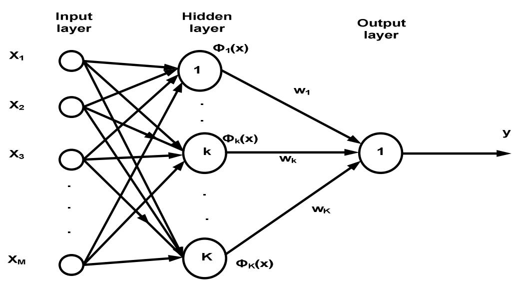


Fig. 2 General Regression Neural Network (GRNN) [29]

In summary, the design procedure for the GRNN based controller has the following steps:
1: applying the model predictive control technique to control the speed of the indirect field oriented linear induction motor IFOLIM drive.
2: Obtaining the performance of the MPC controller in different operating condition for obtaining training and test data .
3: Training the neural network according to Fig. 3 (off-line training) and testing it.
The design strategy includes enough flexibility to set the desired robust performance and gives a flexible controller with simple structure. Due to its practical merit, the proposed method easy and can be used in the real world LIM drive.

6. SYSTEM CONFIGURATION

Figure (4) shows the block diagram of an indirect field oriented LIM drive. It consists of LIM, current controlled voltage source inverter, hysteresis current controller, field orientation mechanism, and coordinate translators. A linear speed sensor has been employed for measuring and providing the speed signal necessary for closed loop control. The measured speed is compared to the reference speed, and their difference is fed to the GRNN controller in order to obtain the force current command i_q^*. The flux current command i_d^* is set at rated value. The force and flux current commands are used to obtain the slip command using (10). This latter is added to the actual speed, and the sum is integrated to obtain the field angle θ_e. Therefore the commanded phase currents are obtained using coordinate translation of i_d^*, and i_q^*. The 3-phase primary currents are measured and fed to hysteresis current controller. The current controlled pulse width modulation with hysteresis controller regulates the actual primary phase currents to closely follow the sinusoidal commanded currents. Using indirect field oriented technique, the transfer function of the motor can be deduced using (5) as:

$$\text{Transfer function} = \frac{v}{F_e - F_L} = \frac{1}{Ms+D} \qquad (20)$$

For easy implantation, the simplified linearized model of the LIM described by (20) is employed in the structure of the MPC controller which used for the off-line training for the proposed GRNN controller as shown in Fig. 3.

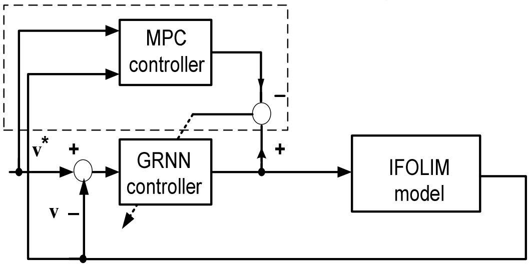


Fig. 3. GRNN control design problem based on MPC technique.

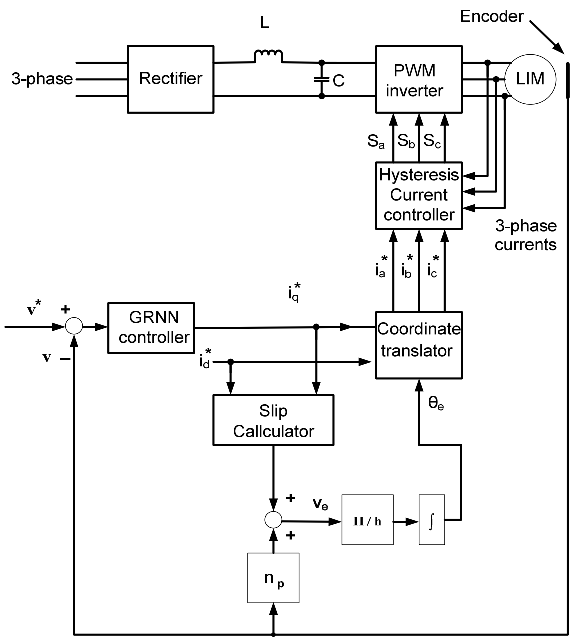


Fig. 4 Block diagram of the indirect field oriented Linear induction motor drive

7. RESULTS AND DISCUSSIONS

Computer simulations have been carried out in order to validate the effectiveness of the proposed scheme. The Matlab / Simulink software package has been used for this purpose. The data of the LIM used for simulation procedure are [17]: 3-phase, Y-connected, 8-pole, 3-kW, 60-Hz, 180-V, 14.2 A. The motor detailed parameters are listed in table .1.
The parameters of the MPC controller are set as follows:
Prediction horizon = 60,
control horizon = 40,
Weights on manipulated variables = 0 ,
Weights on manipulated variable rates = 0.1 ,
Weights on the output signals = 100,
Sampling interval = 0.0001 sec.
Constraints are imposed over the developed force, and motor speed as :
Max. developed force = 1000 N.
Min. developed force = 0 N.
Max. mover speed = 1.5 m/sec.
Min. mover speed = -1 m/sec.
The parameters of the proposed GRNN controller are:
Input speed error (e_v = reference speed – actual speed)
Output the force current command i_q^* .
Mean square error of the GRNN = 1 * 10^{-7}.
According the off-line training and testing data, the GRNN controller has enough neurons in the hidden layer.

Firstly, the dynamic response of the system is investigated under the condition of load disturbance effect. Figure (5)

Table. 1 Parameters and data of the LIM

$R_s(\Omega)$	5.3685	Pole pitch, $h(m)$	0.027
$R_r\ \Omega)$	3.5315	Total mass of the mover, $M(kg)$	2.78
L_s(H)	0.02846	viscous friction and iron-loss coefficient, $D(kg/s)$	36.045
L_r (H)	0.02846	Force constant, $k_f(N/wb.A)$	593.35
L_m (H)	0.02419	Rated secondary flux, (wb)	0.056

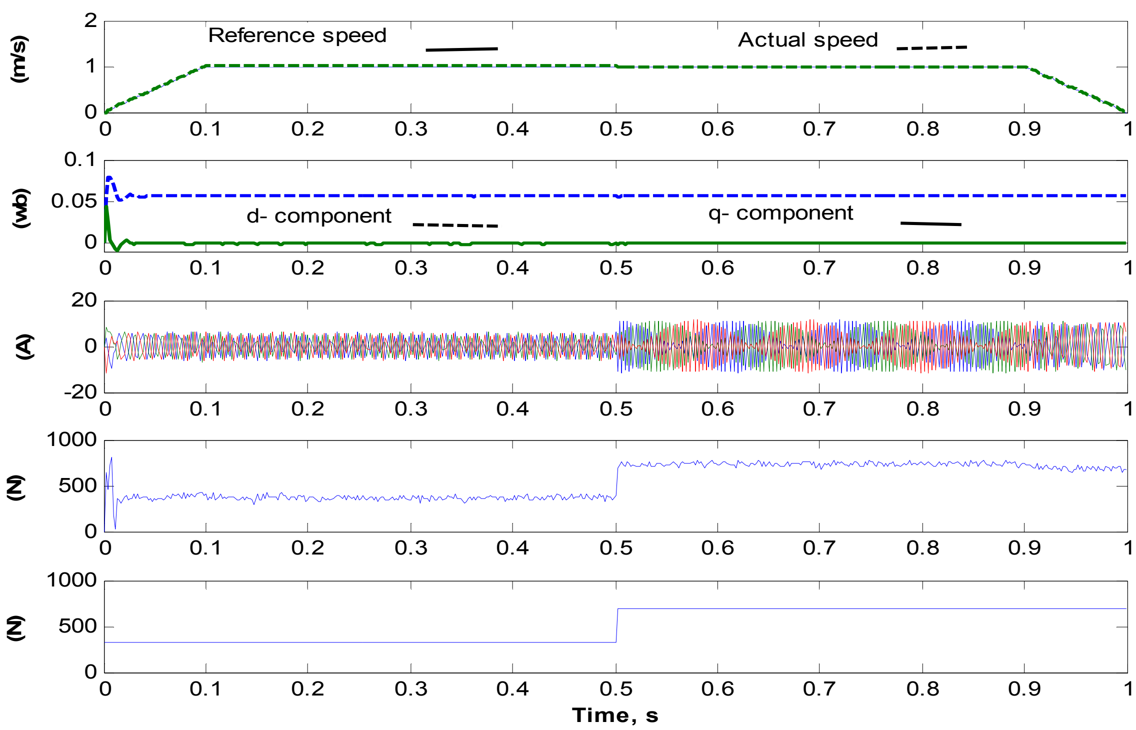


Fig. (5) Dynamic responses of the proposed system at load disturbance.

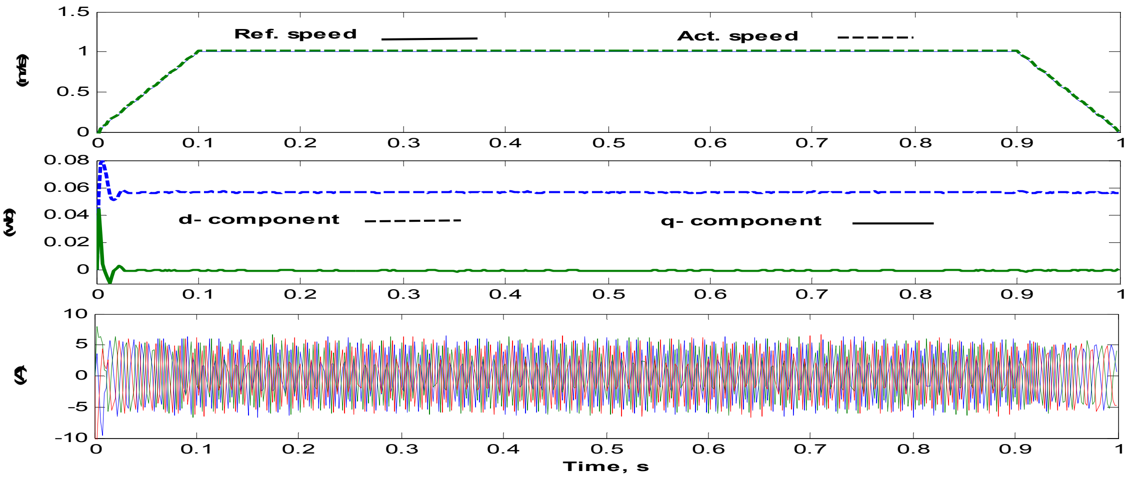
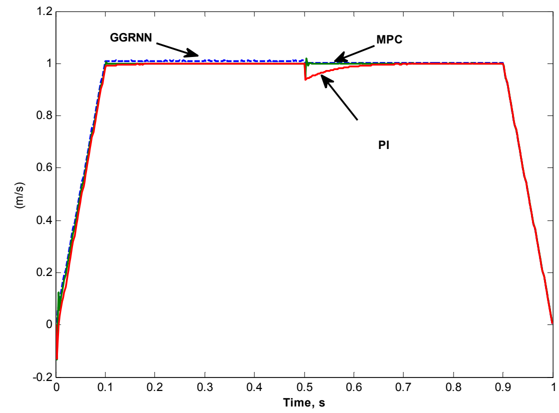


Fig. (6) Dynamic responses of the proposed system under parameters mismatch condition shows the simulation results of the proposed scheme in this case assuming nominal motor parameters. The LIM is assumed to start at t=0 and accelerated up to 1 m/sec in the first 0.1 second, then the motor speed is kept constant at this value during the next 0.8 second, and decelerated till zero speed is reached during the next 0.1 sec (short acceleration and deceleration times are suitable for the used small LIM). The results from the top to the bottom are: the reference and actual speeds, d-q secondary flux components, 3-phase primary currents, developed force and the load force.

The load force is assumed to be stepped from 350 N to 700 N at t = 0.5 second. It has been noticed that the reference and actual speeds are aligned and good tracking performance has been achieved in spite of the load disturbance. Also the figure indicates that the actual d-axis secondary flux is equal to the set value (0.0568 wb) while the actual q-axis flux is kept zero during the simulation period. This means that the field orientation condition has been realized which leads to high dynamic performance drive. The figure reports also that the developed force follows the increase of the load disturbance. Similarly, the primary phase currents respond quickly to the speed and load variations.

Secondly, the robustness of the LIM with the GRNN controller is investigated during parameters uncertainty. In this case, the secondary resistance is increased by 25% in the LIM model, while it is kept at its nominal value in both of the controller and the slip calculator. Also, the mover mass is increased by 50% only in the motor model.
Figure. (6) depicts the response of the GRNN controller in this case of parameters uncertainty at constant load ($F_L = 300N$). It has been indicated that very fast response has been achieved using the GRNN controller. Also, the waveforms of the primary currents are free of any ripples. In addition, the actual q-axis and d-axis indicate that the field orientation condition has been realized.
Thirdly, the tracking performance of the GRNN controller is compared with the response of PI controllers. The load force is assumed to stepped from 350 N to 700N at t = 0.5 second. Figure (7-a) shows the GRNN response as well as the MPC and PI responses under such case of study. It has been noticed that with the MPC controller, the reference and actual speeds are aligned and good tracking performance has been achieved even at the instant of load disturbance. This is because the MPC provides feedback compensation for the load disturbance. With the GRNN gives good tracking even after the change of the load . In contrast, with PI controller needs a period of time (≈.15 sec.) in order to attain the steady state value either after the load disturbance took place as obtained clearly in Fig. 7-b .



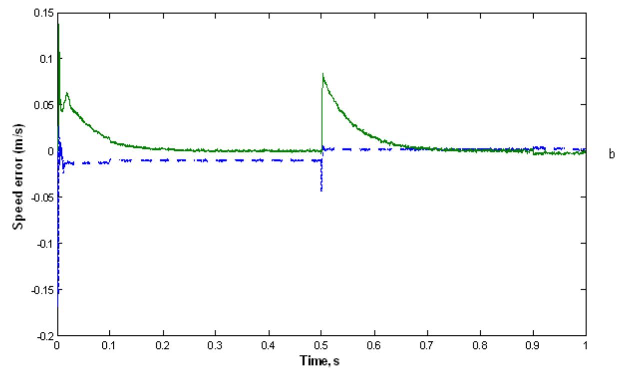


Fig. 7: a) GRNN response versus MPC and PI responses at load disturbance.
b) speed error (solid line) for PI and (dashed line) for GRNN.

8. CONCLUSIONS

In this paper, a GRNN based controller is used to control the speed and thrust output of the linear induction motor drive. The speed control problem first is formulated as an optimization control problem via a model predictive control technique and the proposed GRNN controller is then trained based on samples obtained from applying the MPC controller to the indirect field oriented LIM drive system in different operating conditions under load variations. This control strategy includes enough flexibility to set the desired level of robust performance. The proposed controller has been tested through mismatched parameters and load force disturbance. Simulation results show that the proposed GRNN controller has the advantages of the MPC controller such as; very fast response, robustness against parameter uncertainties and load changes, well tracking of speed trajectory at all speeds and has almost no current and force ripples. In additional, the proposed controller has a simple structure that is easy to implement. A performance comparison between the proposed controller and a conventional integral control scheme is carried out confirming the superiority of the proposed GRNN controller.

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