A Global ANN Algorithm for Induction Motor Based on Optimal Preview Control Theory

M. M. Negm, A. H. Mantawy, and M. H. Shwehdi

***Abstract*—In this paper a global Artificial Neural Network (ANN), algorithm for on-line speed control of a three-phase induction motor (IM), is proposed. This algorithm is based on the optimal preview controller. It comprises a novel error system and vector control of the IM. The IM model includes three input variables, which are the stator angular frequency and the two components of the stator space voltage vector, and three output variables, which are the rotor angular velocity and the two components of the stator space flux linkage. The objective of the proposed algorithm is to achieve rotor speed control, field orientation control and constant flux control. In order to emulate the characteristic of the optimal preview controller within global and accurate performance system, a neural network-based technique for the on-line purpose of speed control of IM, is implemented. This technique is utilized based on optimizing the speed control problem using the optimal preview control law. The numerical solution is used to train a feed ANN using the radial basis method. Successive trained data is utilized to obtain global stability operation for the IM over the whole control intervals. This data includes, several desired speed trajectories and different load torque operations in addition to the motor parameter variations. Digital computer simulation results have been carried-out to demonstrate the feasibility, reliability and effectiveness of the proposed global ANN algorithm.**

***Index Terms*—Radial basis NN algorithm, optimal control, preview control, vector control, induction motor model.**

I. Introduction

UNTIL-NOW, the induction motor (IM) drives with an inverter has been a representative variable speed drive system among the AC motor drives owing to their robustness and low price. The modern control strategy also has rendered some speed control solutions to the IM. Among the various applications, the IM's used in the hoist, cranes and electric vehicles are often driven above their ratings. During the over-load region, it is not easy to obtain the exact rotor flux information especially without speed measurements due to the air-gap flux saturation. Research in IM, for the past two decades, has focused on improving the different field-oriented schemes to remedy their problems [1]-[14].

In particular, much work has been done in decreasing the sensitivity of the control system to the motor parameter variations and model uncertainties [15], [16].

There are numbers of trends and tradeoffs involved in implementing the different forms of field oriented control. First, most of the field orientation methods require precise knowledge of either the rotor position or speed. This implies the need for speed sensors such as tacho-generators, resolvers or digital shaft encoders. Second, the direct field-oriented scheme requires the rotor flux, which is directly measured using hall-effect sensors or search coils for the slip ring motor. Third, the implementation of direct field orientation uses an open loop integration of the machine voltage to estimate the flux, which gives problems at low speeds. Finally, although the indirect field oriented control scheme is simple and preferred, its performance is highly dependent on an accurate knowledge of the machine parameters [17]-[19].

In contrary, however, a scalar control technique of IM, voltage/frequency (V/F) control or constant flux control, is an open loop control. This technique has been widely used for low performance, low power and low cost industrial drives, which are classified as general purpose drives. No feedback speed is necessary for such technique. Nevertheless, it is generally classified as an open loop scalar control scheme. IM drive systems based on full digital control have reached the status of a maturing technology in a board range of applications ranging from low-cost to high-performance systems [10], [14].

Continuing research has concentrated on the elimination of the speed sensor at the motor shaft and other IM variable sensors without deteriorating the dynamic performance of the drive system [10]-[15], [18]-[24]. The advances in micro-processors and power electronics have permitted the implementation of modern techniques for induction machines, such as, field oriented control [1]-[14], indirect field control [17]-[19], vector control [1]-[7], [15], [19], [20] and sensorless control [10]-[15], [18]-[23]. Applications of modern control theory to IM's, such as, optimal control [1]-[3], adaptive control [4], [9], [11], [12], [20]-[22], variable structure control [5], fuzzy control [18], [19], observers [12], [14], [22], neural network control [1], and others, have recently been published. There are two important points for the speed control of IM's. The first is the capability of highly accurate speed control, while the second is to maintain a constant speed even if subject to disturbances.

A field oriented control technique is synthesized in this paper using the vector method and an optimal control law that requires deriving the state equation of the 3-phase IM on the synchronous frame. Preview feed-forward steps are introduced into the control law to enhance the transient response and to improve the robustness of the controlled system. The IM is described as a three input, three output controlled model. The state equations of IM suitable for voltage control are derived based on the vector method. Furthermore, deriving the state equations on a

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synchronously rotating reference frame, and trying to maximize the developed torque over the whole control range construct the field-oriented control system. The objective of the controlled system is to achieve rotor speed control, field orientation control and constant flux control. Using a new error system technique cures the adverse phenomena that are caused due to parameter uncertainties and un-modeled dynamics. This preview controller utilizes few future values of the desired and disturbance signals. The desired signal is the required rotor angular velocity and the required two components of the stator space flux linkage. The disturbance signal is the mechanical load torque subjected to the IM. The universal nonlinear approximation capabilities and the nonlinear nature of the speed control problem motivate the use of neural networks. Radial basis functions neural networks (RBFNN) have been developed based on the theory of RBF approximation for real multivariable function approximation. The training of the RBFNN was accomplished by using three input three-output data pattern. The training was successful over a large range of training data. Results of tests conducted over several data testing range have shown accurate results and fast performance in predicting the controller output variables. Robustness of the proposed controller is indicated with parameters variations, un-modeled dynamics and with load variations and rotor speed variations. Extensive computer simulations are made to demonstrate the robustness and feasibility of the proposed controlled system.

II. State Space Model of the IM

The state space model of the 3-phase IM can be derived on the basis of the vector method in a synchronously rotating reference frame (α, β) as, [3]:

$$v_s = r_1 i_s + \frac{d\psi_s}{dt} + j\omega_1 \psi_s \tag{1}$$

$$v_r = r_2 i_r + \frac{d\psi_r}{dt} + j\omega_s \psi_r \tag{2}$$

$$\psi_s = L_s i_s + L_m i_r \tag{3}$$

$$\psi_r = L_m i_s + L_r i_r \tag{4}$$

$$T = \frac{3}{2} p\, Im(\psi_s^* i_s) = J\frac{d\omega_r}{dt} + F\omega_r + T_L \tag{5}$$

where v_s and i_s are the stator space voltage and current vectors, respectively, while v_r, i_r are the rotor space voltage and current vectors, respectively. ψ_s, ψ_r are the stator space flux vector and the rotor space flux vector, respectively. Furthermore, the symbols T and T_L denote the mechanical torque and load torque respectively, while J, F are the moment of inertia and viscous friction, respectively. Also, ω_1 and ω_r are the stator and rotor angular frequencies, respectively, while r_1 and r_2 are the stator and rotor resistances per phase, respectively. Finally, the slip angular frequency of the IM is given by $\omega_s = \omega_1 - \omega_r$.

III. Optimal Preview Control Law

The objective of the field-orientation control is to keep the magnitude of the stator flux linkage constant while the position of rotor angular frequency changes arbitrary. This orientation can be achieved by adjusting the stator space voltage vector and the stator frequency arbitrarily [3]. Therefore, to achieve the above objective, the flux component $\psi_{s\beta}$ must be equal zero, while the flux component $\psi_{s\alpha}$ is kept constant to attain maximum torque with changing the stator current components $i_{s\beta}$ and $i_{s\alpha}$ simultaneously. The discrete state space model (6), of the 3-phase IM is given from the linearized state-space model of (1)-(5), [3].

$$x(k+1) = Ax(k) + Bu(k-1) + Cd(k) \tag{6}$$

While the output variable is considered as given by,

$$y(k) = Ex(k) \tag{7}$$

where k represents the sampling time kT, $k = 0, 1, 2, \ldots,$ and T is the sampling period and the dimensions of matrices A, B, C and E are (5×5), (5×3), (5×1) and (3×5), respectively. The state variable $x(k)$, the input variable $u(k)$, the output variable $y(k)$ and the disturbance signal $d(k)$, are given by:

$$x(k) = [\omega_r(k)\ \psi_{s\alpha}(k)\ \psi_{s\beta}(k)\ i_{s\alpha}(k)\ i_{s\beta}(k)]^t;$$

$$u(k) = [\omega_1(k)\ v_{s\alpha}(k)\ v_{s\beta}(k)]^t$$

$$y(k) = [\omega_r(k)\ \psi_{s\alpha}(k)\ \psi_{s\beta}(k)]^t;$$

$$v_s(k) = v_{s\alpha}(k) + jv_{s\beta}(k);\ i_s(k) = i_{s\alpha}(k) + ji_{s\beta}(k)$$

$$\psi_s(k) = \psi_{s\alpha}(k) + j\psi_{s\beta}(k)\ ;\ d(k) = T_L(k)$$

Note that the input vector $u(k)$ is delayed by one sampling period to compensate for the micro-processor's execution time.

The optimal preview controller $u(k)$, for the system (6)-(7), is synthesized according to the MIMO system as follows [3]. Let the error signal e(k):

$$e(k) = R(k) - y(k) \tag{8}$$

where $e(k) = [e_{\omega r}(k)\ e_{s\alpha}(k)\ e_{s\beta}(k)]^t$, and the reference signal is $R(k) = [\omega_r^d(k) \psi_{s\alpha}^d(k) \psi_{s\beta}^d(k)]$. The superscript "d" denotes the desired value and "t" is the transposition.

Using (7) to get the first difference of (8) and then the substitution from (6) gives,

$$\begin{aligned}\Delta e(k+1) = \Delta e(k) + F_a \Delta x(k) + F_b \Delta u(k-1)\\ + F_c \Delta d(k) + \Delta z(k+1)\end{aligned} \tag{9}$$

where

$$F_a = F(A - I_5);\ F_b = FB;\ F_c = FC;\ F = -E$$

$$\Delta z(k+1) = \Delta R(k+1) - \Delta R(k);\ \Delta = (1 - q^{-1}).$$

Then error system (10), is constructed from (6) and (9).

$$X(k+1) = \Phi X(k) + \theta u(k) + G_r \Delta z(k+1) + G_d \Delta d(k) \tag{10}$$

where

$$X(k+1) = [e(k)\ \Delta e(k+1)\ \Delta x(k+1)\ \Delta u(k)]^t$$

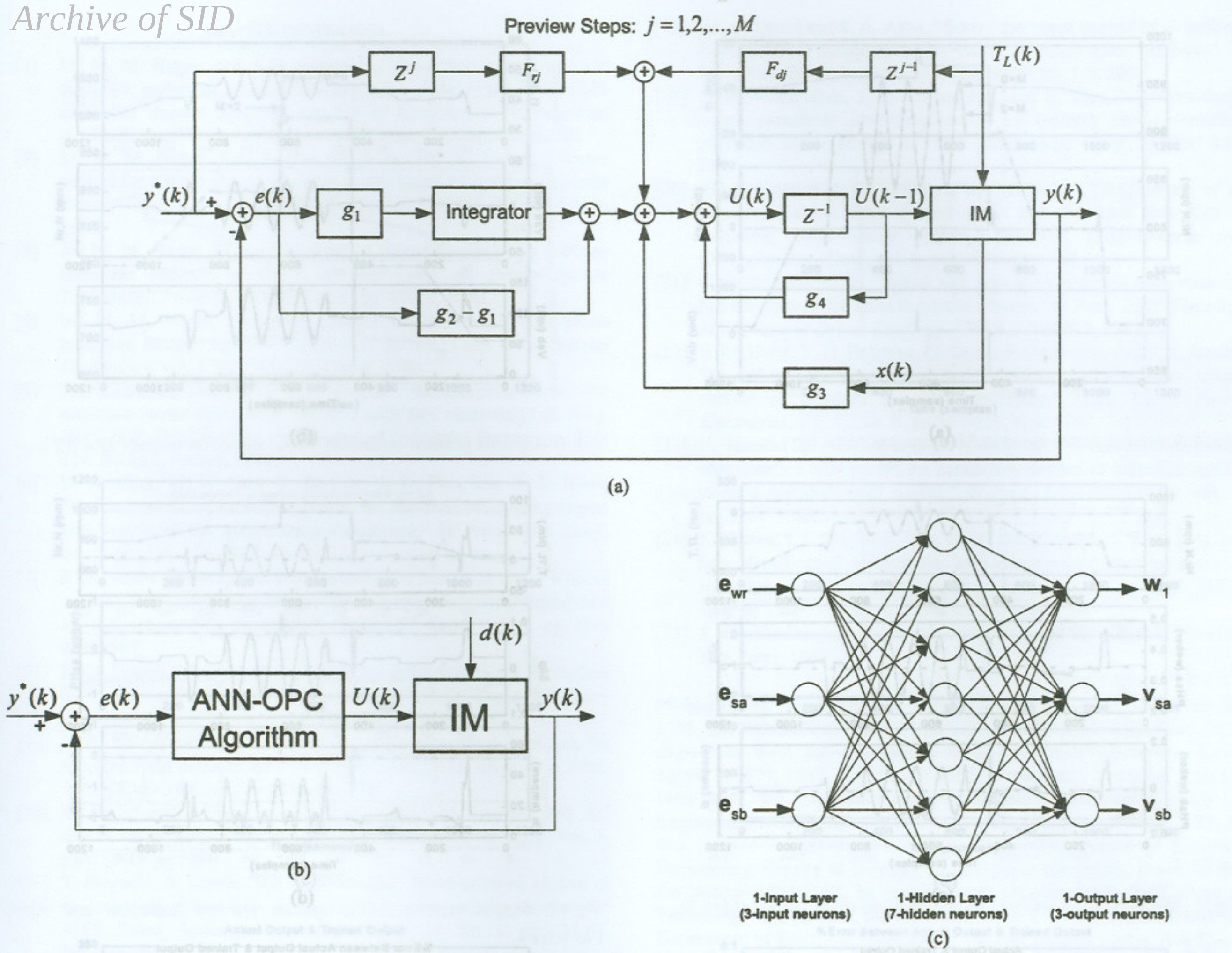

Fig. 1. (a) Optimal controller with preview feed-forward steps, (b) global ANN optimal preview control algorithm, (c) diagram of the proposed neural network.

$$\Phi=\begin{bmatrix} I_3 & I_3 & 0 & 0\\ 0 & I_3 & F_a & F_b\\ 0 & 0 & A & B\\ 0 & 0 & 0 & 0\end{bmatrix};\theta=\begin{bmatrix}0\\0\\0\\I_3\end{bmatrix};G_r=\begin{bmatrix}0\\I_3\\0\\0\end{bmatrix};G_d=\begin{bmatrix}0\\F_c\\C\\0\end{bmatrix}.$$

To implement the optimal preview control law, the following selected performance index J_d, is to be minimized subject to the constraints given by (10).

$$J_d=\sum_{k=0}^{\infty}[X(k+1)^t QX(k+1)+\Delta u(k)^t R\Delta u(k)]$$

where the weighting matrices $Q(14\times14)$, $R(3\times3)$ and $q(3\times3)$ are given by:

$$Q=\begin{bmatrix} q & q & \\ q & q & \\ & & 0\end{bmatrix};\; q=\begin{bmatrix} q_1 & 0 & 0\\ 0 & q_2 & 0\\ 0 & 0 & q_3\end{bmatrix};\; R=\begin{bmatrix} r_1 & 0 & 0\\ 0 & r_2 & 0\\ 0 & 0 & r_3\end{bmatrix}$$

Accordingly, the minimization process gives the following optimal preview controller:

$$\Delta u(k)=GX(k)+G_1W(k+1)+\sum_{j=2}^{M}[G_j[K_1]^{j-2}W(k+j)] \quad (11)$$

where

$$W(k+1)=G_r\Delta z(k+1)+G_d\Delta d(k)$$

Feedback Gain : $\mathbf{G}=-\gamma\Theta^t\mathbf{K}\Phi$

Feedforward Gain : $\mathbf{G}_1=-\gamma\Theta^t\mathbf{K}$

$\mathbf{G}_2=-\gamma\Theta^t\Phi^t\lambda$

$\mathbf{G}_j=\mathbf{G}_{j-1}\mathbf{K}_1;\, j=3,4,...,M$

$\mathbf{K}_1=\mathbf{K}^{-1}\varphi^t\lambda$, $\mathbf{K},\gamma$ and λ are the steady state solution of the following Riccati equation

$$K(i)=Q+\Phi^t\lambda(i+1)\Phi$$

$$\lambda(i+1)=K(i+1)[I_{14}-\theta\gamma(i+1)\theta^t K(i+1)].$$

$$\gamma(i+1)=[R+\theta^t K(i+1)\theta]^{-1}$$

The real time optimal preview control law, (12), can be derived by induction from (11), such that:

$$u(k)=g_1\sum_{i=0}^{k}e(i)+(g_2-g_1)e(k)+g_3x(k)+ g_4u(k-1)+\sum_{i=1}^{M}F_{ri}[\Delta R(k+i)-\Delta R(i)] +\sum_{i=1}^{M}F_{di}[d(k+i-1)-d(i-1)] \quad (12)$$

where $F_{ri}=G_iG_r;\, F_{di}=G_iG_d;\quad i=1,2,..,M,\quad M\geq1$, is the preview feed-forward steps.

The control system structure is implemented from (12), as indicated in Fig. 1(a).

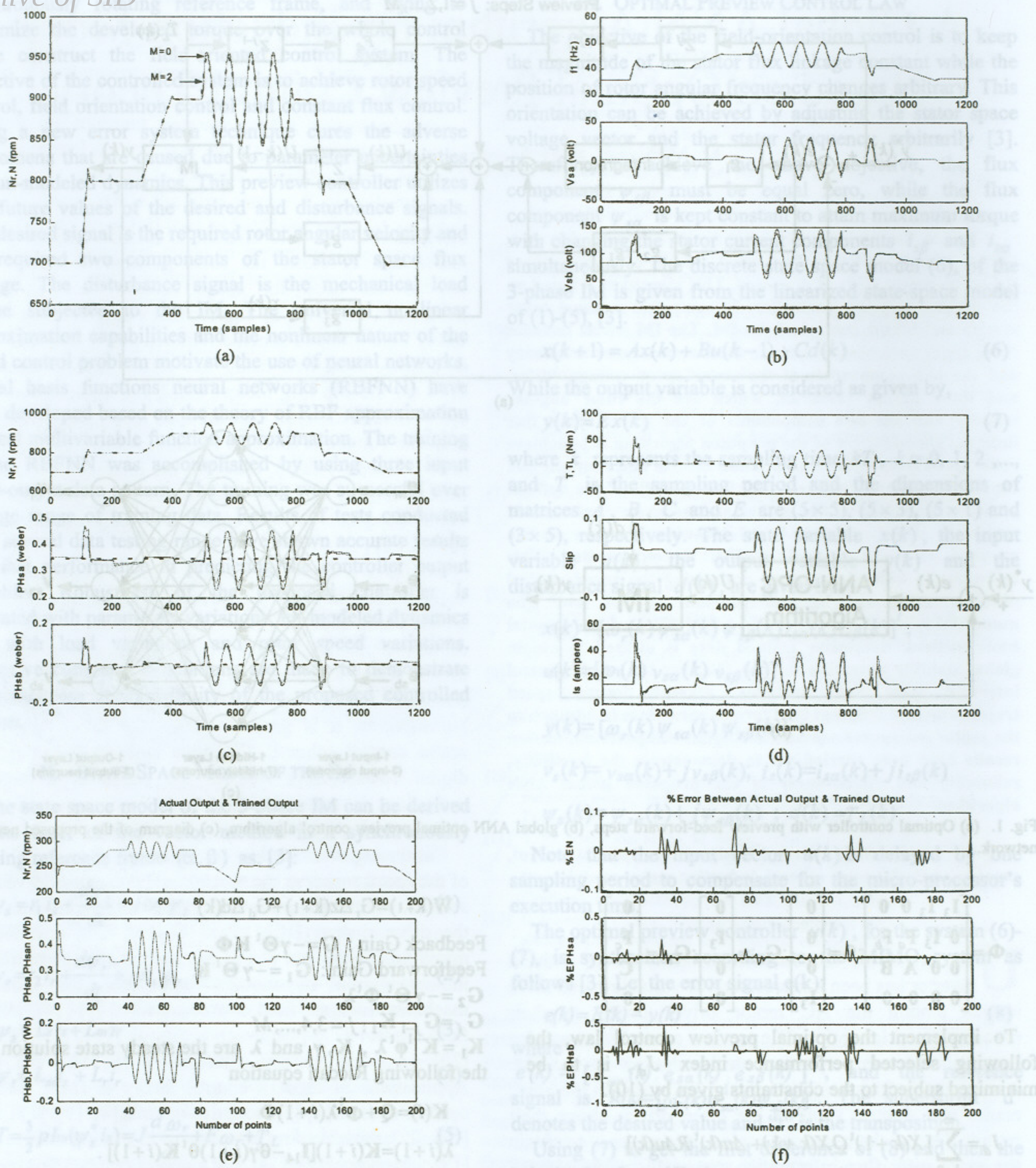

Fig. 2. $M=0,2$, (a) Reference motor speed and its response, (b) input variables, (c) desired output variables and their responses, (d) mechanical torque, load torque, slip and stator current, (e) optimal preview controller output and ANN output, (f) output error between optimal preview controller and ANN.

IV. Global ANN Algorithm

The multi-layer feed-forward global ANN of the optimal preview controller with radial basis training algorithm is used. The ANN algorithm contains an input layer with three input neurons, a hidden layer and an output layer with three output neurons [1]. Number of the hidden layers or hidden neurons is defined by trial and error, where the suitable starting number is $2j+1$; where j is number of the input neurons [25]. The three ANN inputs training parameters are the error of rotor speed and the error of the two stator flux components (output error $e(k)$). The three ANN output parameters are the stator angular frequency and the two stator voltage components (input variable $u(k)$), see Figs. 1(b) and 1(c). A MATLAB® program is written to train the ANN algorithm with numerical results obtained from the optimal preview control law (12). Several runs have been carried-out under different operating conditions (include different desired speed trajectories, variable load torque operations and motor parameter variations), to find the global ANN configuration setting.

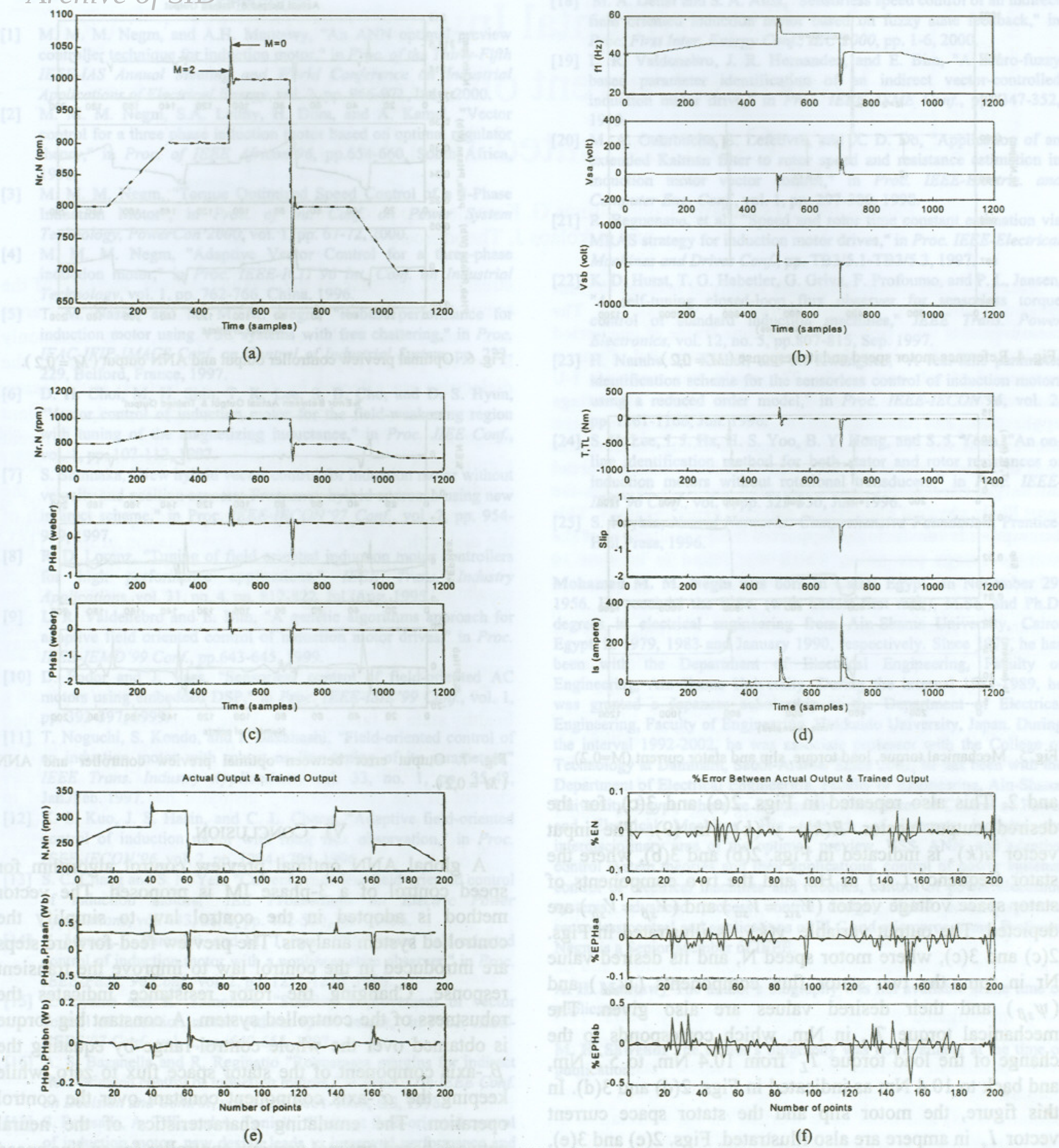

Fig. 3. $M = 0,2$, (a) Reference motor speed and its response, (b) input variables, (c) desired output variables and their responses, (d) mechanical torque, load torque, slip and stator current, (e) optimal preview controller output and ANN output, (f) output error between optimal preview controller and ANN.

V. Simulation Results

The proposed optimal preview control law is used in this paper to control a 1.1 kW, 1000 rpm, 200 V line voltage, 6-pole, 50Hz, 3-phase squirrel cage IM. Its parameters are; $J = 0.0179$ Kg-m^2, F= 8E 04 Nm/rad/sec; $r_1 = 0.2842\,\Omega$, $r_2 = 0.2878\,\Omega$, $L_m = 26.8$ mH, $L_s = 28.3$ mH, $L_r = 28.8$ mH; $\varphi_{s\beta}^d = 0$, $\varphi_{s\beta}^d = 0.285$ Web.

MATLAB® simulation results, Figs. 2 to 7, are obtained on the basis of (12) with the sampling time T = 1 msec, and the weighting factors, in (12), are $r_1 = r_2 = r_3 = 1$ and $q_1 = 10$, $q_2 = q_3 = 2$. The horizontal line in these figures represents the time in samples. Furthermore, the rotor resistance is changed from $r_2 = 0.2878\,\Omega$ to $r_2 = 1.5 \times 0.2878\,\Omega$ starting from the sampling instant 450; while the load torque T_L is changed abruptly from the full load value (10.4 Nm), to the half load (5.2 Nm) starting at the sampling instant 400, and back to 10.4 Nm starting from the sampling instant 800. Effect of the optimal preview controller is indicated with preview steps $M = 0,2$. In Figs. 2(a) to 2(d) and Figs. 2(a) to 2(d), the dotted line represents response of the motor variables with $M = 0$, while the solid line is taken for the same variables with $M = 2$. Additional dotted lines in Figs. 2(a) and 3(a), indicate the desired rotor speed response N_r, in rpm, while its response N, is indicated in solid line with $M = 0$

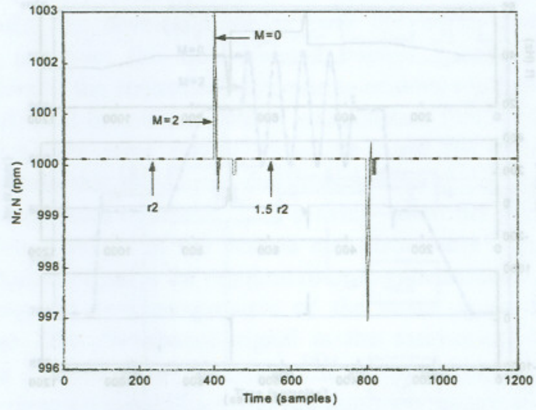

Fig. 4. Reference motor speed and its response ($M = 0,2$).

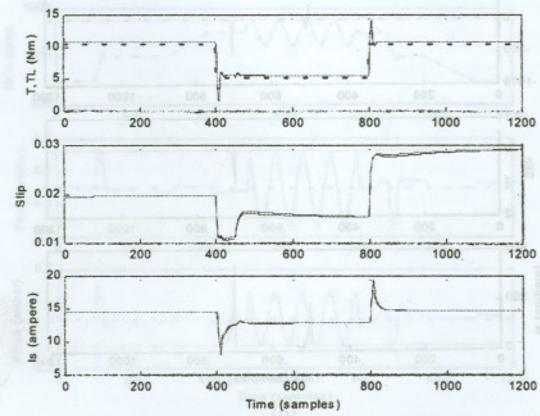

Fig. 5. Mechanical torque, load torque, slip and stator current (M=0,2).

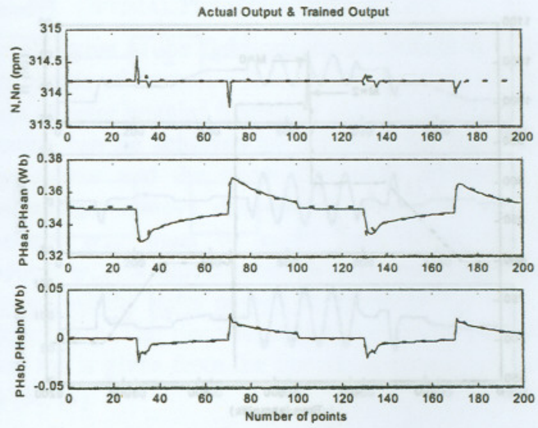

Fig. 6. Optimal preview controller output and ANN output ($M = 0,2$).

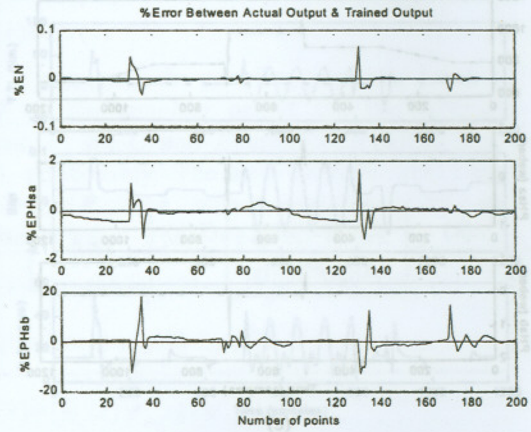

Fig. 7. Output error between optimal preview controller and ANN ($M = 0,2$).

and 2. This also repeated in Figs. 2(c) and 3(c), for the desired output vector $R(k) = y^*(k)$, in (9). The input vector $u(k)$, is indicated in Figs. 2(b) and 3(b), where the stator frequency (f_1) in Hz, and the two components of stator space voltage vector ($V_{s\alpha} = V_{sa}$) and ($V_{s\beta} = V_{sb}$) are depicted. The output variable $y(k)$, is illustrated in Figs. 2(c) and 3(c), where motor speed N, and its desired value Nr in rpm, the two stator flux components ($\psi_{s\alpha}$) and ($\psi_{s\beta}$) and their desired values are also given. The mechanical torque T, in Nm, which corresponds to the change of the load torque T_L from 10.4 Nm, to 5.2 Nm, and back to 10.4 Nm as indicated in Figs. 2(d) and 3(d). In this figure, the motor slip and the stator space current vector I_s in ampere are also illustrated. Figs. 2(e) and 3(e), depict the three actual outputs of the IM under the optimal preview controller. Their trained outputs of the NN algorithm are also coincidentally indicated in the same figures. The beginning 100 points in these figures are taken with $M = 0$, while the next 100 points are obtained with $M = 2$. Figs. 2(f) and 3(f), illustrate the percentage error between the actual output and its trained output for the three variables. Two different patterns of the desired motor speed are demonstrated in Figs. 2(a) and 3(a), to show the tracking performance of the motor speed using the proposed algorithm. Effect of changing the rotor parameter is also indicated to demonstrate the robustness of the control system. The rotor resistance r_2 is changed to $1.5 \times r_2$ after the sampling instant 450 as in Figs. 5 to 7, with constant motor speed to, to investigate the robustness of the proposed control algorithm.

VI. Conclusion

A global ANN optimal preview control algorithm for speed control of a 3-phase IM is proposed. The vector method is adopted in the control law to simplify the controlled system analysis. The preview feed-forward steps are introduced in the control law to improve the transient response. Changing the rotor resistance indicates the robustness of the controlled system. A constant big torque is obtained over the whole control range by equating the β -axis component of the stator space flux to zero, while keeping the α -axis component constant over the control operation. The emulating characteristics of the neural network-based optimal preview controller for on-line speed control of IM indicated good tracking response. However, the numerical solution, which is used to train a feed ANN using the radial basis method, gave accurate and precise performance operation, under several desired speed trajectories and different load torque operations in addition to the motor parameter variations. Furthermore, successive trained data is utilized, and global stability operation for the IM over the whole control intervals is achieved. The proposed algorithm is found to be suitable for optimal preview control solution of IM. Coincidental results between the desired values and their responses are obtained. Computer simulation results are made for speed control, field orientation control and constant flux control.

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