



Modeling Induction Motors

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Abstract: In this paper, a novel technique for on-line estimation of most electrical parameters of an induction motor is presented. Such estimation is important to achieve high performance drive systems. The proposed technique uses Volterra neural networks (VNN). This technique is based on the measurements of the stator voltages, currents and motor speed with no need for state-space modeling. Moreover, the VNN is implemented to relate the steady-state performance characteristics of an induction motor to their inputs. Simulation and practical results establish the validity of the proposed technique and show reasonable accuracy of the estimated parameters as well as excellent steady-state performance characteristics.

Keywords: Induction motor, Parameter estimation, Volterra series, neural networks.

1. Introduction

Induction motors are known to be superior to their DC counterparts concerning, ruggedness, reliability, cost, size and output power per weight. This has motivated the study of induction motor performance in various drives [1-3]. In variable speed induction motor drives, it is often required to know the accurate values of motor parameters to realize high performance drive systems.

Traditionally, machine parameters have been determined by performing no-load tests and locked rotor tests. These experiments are not convenient because they require human electrical measurements and intervention on the machine. The machine service must be interrupted while the tests are performed. Moreover, it is difficult to perform the locked rotor tests on large power machines. The locked rotor test gives a very high slip frequency, which increases the skin-effect influence on the rotor resistance. This leads to inadequate operating conditions and inaccurate parameter estimation. In [4] reviews of numerous methods that have been proposed to identify the motor parameters are introduced. In most of these methods, only the estimation of one parameter is considered (rotor time constant or resistance).

Recent works for estimating the induction motor parameters show that the extended Kalman filter can be successfully applied to simultaneous estimation of all electrical parameters [5-7]. The main advantage of this method is to allow regular operating conditions, without disturbing test signals. This is very important for on-line estimation and real-time controller tuning. However, this method is computationally demanding, as the estimator uses a fifth-order state-space model of the induction machine and the algorithm involves a significant number of matrix multiplications and additions. This motivates the development of a suitable method for on-line estimation of all electrical machine parameters that can reduce the amount of calculations.

In this paper, a novel technique for estimating most electrical parameters of an induction motor is presented. The proposed technique employs Volterra neural networks [8]. Several advantages are immediately apparent on adopting this technique. No state-space models are required. Explicit formulae relating the acquired model performances and parameters can be

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obtained. Being adaptive, these parameters can be monitored in the real time. The rest of the paper is organized as follows: Section 2 summarizes the essential features of steady state and dynamic models of the induction motor. Section 3 describes the Volterra neural networks. Section 4 introduces the proposed method and presents the results obtained. Finally Section 5 concludes the work.

2. Steady State and Dynamic Models of An Induction Motor

A. Steady State Equivalent Circuit

The steady state motor model can be deduced from the description of the stator and rotor electrical circuits. With this physical approach, five electrical elements are defined as the stator and rotor resistances (R_s and R_r), stator and rotor leakage inductances (L_{ls} , L_{lr}) and a magnetizing inductance (L_m). This definition leads to the usual equivalent circuit for steady-state operation of an induction motor [9]. From this equivalent circuit, one can obtain expressions for the motor torque, stator current, input power factor and efficiency [9].

B. Mathematical Dynamic Model of an Induction Motor

The induction motor can be represented in the stator stationary reference frame (α - β coordinate axes) by a second order differential equation relating the stator input voltages and currents as [10]

$$\frac{d^2 i_s}{dt^2} + g_1 \frac{di_s}{dt} + g_0 i_s = h_1 \frac{dv_s}{dt} + h_0 v_s \quad (1)$$

Where the coefficients of equation (1) are given in the following way

$$\begin{aligned} g_1 &= \frac{R_s L_r + R_r L_s}{\sigma_s} - j\omega_r \\ g_0 &= \frac{L_r R_s}{\sigma_s} \left(\frac{1}{T_r} - j\omega_r \right) \\ h_1 &= \frac{L_r}{\sigma_s} \\ h_0 &= \frac{L_r}{\sigma_s} \left(\frac{1}{T_r} - j\omega_r \right) \end{aligned} \quad (2)$$

These coefficients are functions of the machine parameters and motor speed (ω_r). Where L_s and L_r are stator and rotor self inductance respectively, and are defined by $L_s = L_m + L_{ls}$ and $L_r = L_m + L_{lr}$, $T_r = L_r/R_r$ is a rotor time constant and $\sigma_s = L_s L_r - L_m^2$ is known as leakage index. The stator phase voltages and currents can also be transformed to the stationary reference frame (α - β axes) [18]. The stator voltage and current equations, which are complex, can be written as

$$\mathbf{V}_s = v_{s\alpha} + jv_{s\beta} \quad (3)$$

$$\mathbf{i}_s = i_{s\alpha} + ji_{s\beta} \quad (4)$$

Where $v_{s\alpha}, v_{s\beta}$ are the α -axis and β -axis stator voltage components in the stationary reference frame and $i_{s\alpha}, i_{s\beta}$ are the corresponding currents. Using equations (1)-(4), the second derivative of the stator current, components at constant speed can be derived as

$$\begin{bmatrix} \frac{d^2 i_{s\alpha}}{dt^2} + \omega_r \frac{di_{s\beta}}{dt} \\ \frac{d^2 i_{s\beta}}{dt^2} - \omega_r \frac{di_{s\alpha}}{dt} \end{bmatrix} = \begin{bmatrix} -\frac{di_{s\alpha}}{dt} \left(\frac{dv_{s\alpha}}{dt} + \omega_r v_{s\beta} \right) v_{s\alpha} - i_{s\alpha} - \omega_r i_{s\beta} \\ -\frac{di_{s\beta}}{dt} \left(\frac{dv_{s\beta}}{dt} + \omega_r v_{s\alpha} \right) v_{s\beta} - i_{s\beta} \omega_r i_{s\alpha} \end{bmatrix} \begin{bmatrix} A_1 \\ A_2 \\ A_3 \\ A_4 \\ A_5 \end{bmatrix} \quad (5)$$

$$\text{Where } A_1 = \frac{R_s L_r + R_r L_s}{\sigma_s}, A_2 = \frac{L_r}{\sigma_s}, A_3 = \frac{R_r}{\sigma_s}, A_4 = \frac{R_r R_s}{\sigma_s} \text{ and } A_5 = \frac{L_r R_s}{\sigma_s}$$

Applying the following constraints to equation (5),

$$\text{Constraint 1: } v_{s\alpha} = |V_s| \cos \omega_s t$$

$$\text{Constraint 2: } v_{s\beta} = |V_s| \sin \omega_s t$$

$$\text{Constraint 3: } i_{s\alpha} = |I_s| \cos(\omega_s t - \theta)$$

$$\text{Constraint 4: } i_{s\beta} = |I_s| \sin(\omega_s t - \theta)$$

Where ω_s is the stator supply angular frequency (rad./sec.) and θ is the phase angle between the stator voltage and current components. This results in the following equations:

$$i_{s\alpha} = \frac{1}{(\omega_s^2 + \omega_s \omega_r - A_4)} [A_2 \omega_s v_{s\beta} + A_3 v_{s\alpha} + A_1 \omega_s i_{s\beta} - A_2 \omega_r v_{s\beta} + A_5 \omega_r i_{s\beta}] \quad (6)$$

$$i_{s\beta} = \frac{1}{(\omega_s^2 + \omega_s \omega_r - A_4)} [A_3 v_{s\beta} + A_2 \omega_s v_{s\alpha} + A_1 \omega_s i_{s\alpha} + A_2 \omega_r v_{s\alpha} - A_5 \omega_r i_{s\alpha}] \quad (7)$$

Equations (6) and (7) represent the model of the induction motor. These equations may be put in the form

$$i_{s\alpha} = K_1 v_{s\beta} + K_2 v_{s\alpha} + K_3 i_{s\beta} + K_4 \omega_r v_{s\beta} + K_5 \omega_r i_{s\beta} \quad (8)$$

$$i_{s\beta} = K_2 v_{s\beta} + K_1 v_{s\alpha} + K_3 i_{s\alpha} - K_4 \omega_r v_{s\alpha} - K_5 \omega_r i_{s\alpha} \quad (9)$$

Where

$$K_1 = \frac{A_2 \omega_s}{(\omega_s^2 + \omega_s \omega_r - A_4)} \quad (10)$$

$$K_2 = \frac{A_3}{(\omega_s^2 + \omega_s \omega_r - A_4)} \quad (11)$$

$$K_3 = \frac{A_1 \omega_s}{(\omega_s^2 + \omega_s \omega_r - A_4)} \quad (12)$$

$$K_4 = \frac{-A_2}{(\omega_s^2 + \omega_s \omega_r - A_4)} \quad (13)$$

$$K_5 = \frac{A_5}{(\omega_s^2 + \omega_s \omega_r - A_4)} \quad (14)$$

At constant known motor speed and if the leakage inductance in both stator and rotor circuits are considered the same [9] ($L_s \cong L_r$), equations (10)-(14) may be solved together to obtain the electrical machine parameters in the form

$$R_s = \frac{K_5 \omega_s}{K_1} \quad (15)$$

$$L_s = \frac{K_3 - R_s K_1 / \omega_s}{K_2} \quad (16)$$

$$R_r = \frac{K_2 \omega_r^2 L_s}{K_1} \quad (17)$$

$$\sigma_s = \frac{R_r + K_2 L_s R_s}{(\omega_r^2 + \omega_s \omega_r) K_2} \quad (18)$$

$$L_m = \sqrt{L_s^2 - \sigma_s} \quad (19)$$

3. Volterra Neural Networks

Consider a continuous and smooth mapping on the form

$$y = f(x) \quad ; \quad y \in R^n, \quad x \in R^m \quad (20)$$

Where $y \in R^n$ and $x \in R^m$ indicate that the dimensional space of y and x are n and m respectively. Each output can be expanded in a Taylor series around some fixed-point say $\underline{0} = (0, 0, \dots, 0)$ resulting in

$$\begin{aligned} y_k = f_k(x) = & a_k(0) + \sum_{j_1=1}^m b_k(j_1) x_{j_1} + \sum_{j_1=1}^m \sum_{j_2=1}^m c_k(j_1, j_2) x_{j_1} x_{j_2} + \dots \\ & \dots + \sum_{j_1=1}^m \sum_{j_2=1}^m \dots \sum_{j_r=1}^m q_k(j_1, j_2, \dots, j_r) x_{j_1} x_{j_2} \dots x_{j_r} + \dots \quad ; k = 1, \dots, n \end{aligned} \quad (21)$$

Where $a_k(0) = f_k(0)$, $b_k(j_1)$ are the linear expansion coefficients, $c_k(j_1, j_2)$ are the quadratic expansion coefficients and so on. A truncated version of the original infinite series is always employed. In case of dynamical systems such as a time series, where the vector x may be formed as a collection of past samples, the term Volterra series expansion is used. The expansion coefficients $q(j_1, j_2, \dots, j_r)$ are called the r th order Volterra Kernel. It is noted that the number of coefficients is proportional to m^r . The number of coefficients may be reduced assuming that the expansion coefficients are symmetric, that is all the $q(j_1, j_2, \dots, j_r)$ are the same for all the $r!$ permutations of the indices (j_1, j_2, \dots, j_r) [11]. In this case, equation (21) becomes

$$\begin{aligned} y_k = f_k(x) = & a_k(0) + \sum_{j_1=1}^m b_k(j_1) x_{j_1} + \sum_{j_1=1}^m \sum_{j_2=j_1}^m c_k(j_1, j_2) x_{j_1} x_{j_2} + \dots \\ & \dots + \sum_{j_1=1}^m \sum_{j_2=j_1}^m \dots \sum_{j_r=j_{r-1}}^m q_k(j_1, j_2, \dots, j_r) x_{j_1} x_{j_2} \dots x_{j_r} + \dots \quad ; k = 1, \dots, n \end{aligned} \quad (22)$$

Moreover, a pruned version in which the $q(j_1, j_2, \dots, j_r)$ are zeros for, $j_1 \neq j_2 \neq \dots \neq j_r$, may also be employed [12]. The Volterra series expansion provides an important tool for dealing with nonlinear systems and models. Recently, this expansion has been utilized in many applications [13]-[16], [8].

The Volterra Neural Network (VNN) [8] employs a truncated Volterra series expansion of the input vector. The expanded input vector is then utilized as the actual input to a normal NN connection. The VNN adopts only the linear transfer functions for all the neurons involved. Provided that a sufficient kernel order is employed in Volterra expanding the input vectors, only one layer may be utilized. The linearity of the neurons transfer functions leads to explicit formulas describing the input/target patterns. These formulae are completely determined by the Volterra expansion coefficients after convergence, which are the biases (the a 's in equations (21), (22)) and the weights (rest of the coefficients in equations (21), (22)).

To clarify VNN, let's assume that it is required to associate a size N two-element input pattern $[x_1 \ x_2]$ to a size N two-element desired (target) pattern $[d_1 \ d_2]$ employing VNN. If a symmetric second order kernel Volterra expansion is used, the expanded input vector, X_e according to (22) is:

$$X_e = \begin{bmatrix} 1 & x_1 & x_2 & x_1^2 & x_2^2 & x_1x_2 \end{bmatrix} \quad (23)$$

The expanded input vector is now the new input for a single layer (flat) neural network structure as shown in Fig.1. The number of neurons in the output layer equals the number of elements in the output vectors (two in our example). There are weights $w(m,n)$ connecting the n^{th} expanded input element to the m^{th} output neuron as shown. The output layer neurons employ linear transfer functions that lead to explicit formulas relating the output/desired patterns to the input patterns. Such formulas are the outstanding feature of VNN. The formulas in our example are given in matrix form as

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} w(1,0) & w(1,1) & w(1,2) & w(1,3) & w(1,4) & w(1,5) \\ w(2,0) & w(2,1) & w(2,2) & w(2,3) & w(2,4) & w(2,5) \end{bmatrix} \begin{bmatrix} 1 \\ x_1 \\ x_2 \\ x_1^2 \\ x_2^2 \\ x_1x_2 \end{bmatrix} \quad (24)$$

It is noted that $w(1,0)$ and $w(2,0)$ are the biases. The VNN is trained incrementally. That is, the weights/biases are updated each time an input pattern is presented to the network using the error vector defined in our example as

$$\begin{bmatrix} e_1 \\ e_2 \end{bmatrix}_k = \begin{bmatrix} d_1 \\ d_2 \end{bmatrix}_k - \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}_k \quad ; \quad k \in [1, N] \quad (25)$$

Where, $[d_1 \ d_2]_k^t$ is the k^{th} desired pattern, $[y_1 \ y_2]_k^t$ is the k^{th} output vector and $[e_1 \ e_2]_k^t$ is the k^{th} error vector. The presentations of all N patterns are equivalent to an epoch. Epochs are repeated until a convergence is achieved. After convergence, the error vectors tend to null, the output vectors tend to the desired patterns and the N input/desired pattern association is complete. The equations relating the desired patterns to the input patterns are the same as in (24) with the y vector replaced by the d vector.

The algorithm employed in training the VNN is the LMS-Newton (LMSN) with variable convergence factor [17],[8]. This algorithm achieves a uniform and fast second order convergence using estimates for the Hessian matrix at each update. The LMSN adaptive algorithm [17] has been extended to the multiple input/output cases to match the VNN architecture [8].

4. Induction Motor Characterization Based on The Vnn

This section illustrates the implementation of the VNN in characterizing the induction motor. The first part is a parametric characterization. That is the VNN weights (after training) are used to estimate the actual electrical parameters of the induction motor. The second part is non-parametric. The VNN weights provide a set of equations, which relates a number of induction motor performance criteria to the essential induction motor inputs.

A. Parametric Characterization

The tested motor was a 9.8 HP, 220-Volt, 50-Hz, delta connection, slip-ring induction motor. The rated stator current per phase was 15.1 A at 1450 rpm. A DC generator of about the same rating is coupled to the motor. The equivalent circuit parameters for it have been determined by tests given in [9].

The VNN may be employed to obtain the electrical machine parameters as follows. The stator input voltages, currents and motor speed are measured instantaneously. The measured stator phase voltages and currents are transformed to the corresponding α - β components. Equation (8) has been employed, although equation (9) may be used either. A VNN configuration with four inputs, $v_{s\alpha}$, $v_{s\beta}$, $i_{s\beta}$ and ω_r and one target $i_{s\alpha}$ is constructed ($n = 1$ and $m = 4$). A truncated Volterra expansion of the input up to the second Kernel is implemented. Referring to equation (22) for the symmetric Volterra series expansion and assigning

$$v_{s\beta} = x_1; \quad v_{s\alpha} = x_2; \quad i_{s\beta} = x_3; \quad \omega_r = x_4; \quad i_{s\alpha} = y_1$$

Then the symmetric second order kernel expansion yields (dropping k for simplicity)

$$\begin{aligned} i_{s\alpha} = & a(0) + b(1)v_{s\beta} + b(2)v_{s\alpha} + b(3)i_{s\beta} + b(4)\omega_r + c(1,1)v_{s\beta}^2 + c(1,2)v_{s\beta}v_{s\alpha} + \\ & + c(1,3)v_{s\beta}i_{s\beta} + c(1,4)v_{s\beta}\omega_r + c(2,2)v_{s\alpha}^2 + c(2,3)v_{s\alpha}i_{s\beta} + c(2,4)v_{s\alpha}\omega_r + \\ & + c(3,3)i_{s\beta}^2 + c(3,4)i_{s\beta}\omega_r + c(4,4)\omega_r^2 \end{aligned} \quad (26)$$

The number of input patterns employed is 100, each contains four sample values of the four inputs and the output patterns are the corresponding 100 target current samples. Comparing equations (8) and (26) it is clear that

$$K_1 = b(1); \quad K_2 = b(2); \quad K_3 = b(3); \quad K_4 = c(1,4); \quad K_5 = c(3,4)$$

The rest of the Volterra series expansion coefficients that are not involved in equation (8) have been reset to zero during training to save time. The adaptive session has been run for two epochs only, where an epoch is a complete presentation for all input patterns. Figure 2.a shows the estimated value of stator phase current using VNN and the measured one. From this figure, one can conclude that the estimated and measured values of the stator phase current are in reasonable agreement. This is also proved from Fig. 2.b, which shows the squared error, achieved during the session. After about 20 iterations the error power has been decreased to about -50 dB (relative to unity) meaning that the target current has reached a reasonable accuracy (around 10^{-5}). The coefficients estimated after the two epochs are:

$$K_1 = 1.1773e-001, K_2 = 4.3818e-004, K_3 = 2.5358e-004,$$

$$K_4 = -1.6412e-004 \text{ and } K_5 = 1.4603e-001$$

Equations 15-19 have been employed to estimate the electrical parameters of the induction motor at hand. Table-1 illustrates the estimated values of electrical motor parameters obtained employing the VNN and those obtained experimentally. The third row shows the percentage error results using the VNN. This error is small and tolerable.

This indicates that on line estimation for the induction motor parameters may be achieved by just feeding the voltages and currents to the VNN and monitoring the VNN steady state output. The epoch length is composed of 200 samples. The signals are sampled at 1 kHz. The two epochs required for the steady state thus take just 20 seconds. The computational requirements for estimating the required parameters are not simple.

B. Non-Parametric Characterization

At steady state, it is usually desirable to investigate the performance characteristics of the induction motor. Typical performance characteristics are the motor electromagnetic torque (T_e), stator current (I_s), input power factor (PF) and efficiency (η). The VNN is implemented to relate these performance criteria to the induction motor inputs, typically the stator supply voltage (V_s) and motor slip-speed (S). The VNN configuration implemented employs two inputs (V_s, S) and four targets (T_e, I_s, PF and η). The number of input and target patterns is 100; each is composed of samples measured experimentally at steady state. Again symmetric second order kernel has been implemented. Figure 3, illustrates the excellent match between the outputs of the VNN and the required targets after five epochs (note that the characteristics is plotted against the per-unit speed which is defined as the ratio between actual motor speed and synchronous speed). The epoch is 200 samples and the 1 kHz sampling results in 50 seconds convergence period. That is an on line relation between the induction motor parameters and its inputs are achieved within nearly one minute. The equations relating the targets to the inputs after VNN convergence are given in matrix form as

$$\begin{bmatrix} T_e \\ I_s \\ PF \\ \eta \end{bmatrix} = \begin{bmatrix} 1.6369e+3 & 1.2084e-1 & -5.8105e+3 & -5.97e-4 & 1.3017e-3 \\ 3.7676e+2 & 1.8697e-4 & -7.1965e+2 & 5.3790e-5 & -5.1193e-5 \\ 3.7211e+0 & 2.7945e-4 & -2.4738e+1 & 1.3975e-5 & 1.1262e-5 \\ -1.6366e+0 & 1.7448e-4 & -2.2050e-1 & 1.9739e-5 & 1.7708e-6 \end{bmatrix} \begin{bmatrix} V_s \\ S \\ V_s^2 \\ V_s S \\ S^2 \end{bmatrix} \quad (27)$$

Equation (27) is used to characterize the steady-state model of an induction motor by relating the motor performance characteristics to the motor inputs. This characterization is valid to obtain the motor performance characteristics accurately at any loading conditions. It is worth mentioning here that such explicit equations are impossible to be obtained implementing conventional neural networks.

5. Conclusion

A novel technique for on-line estimation of most electrical parameters as well as deducing the steady-state performance characteristics of an induction motor has been proposed. In the proposed technique, measurements of some essential quantities such as the stator voltages, currents and motor speed are employed in suitable VNN configurations with second order Kernels. Explicit formulae relating the convergent VNN weights and biases to the acquired electrical parameters are provided. Other formulae are also obtained to get the steady state motor torque, stator current, input power factor and efficiency at any supply voltage and motor speed. The accuracy of the estimated parameters using the proposed technique is reasonable compared to the nominal values. An excellent match between the steady-state performance characteristics obtained from the trained VNN and those obtained experimentally has been achieved.

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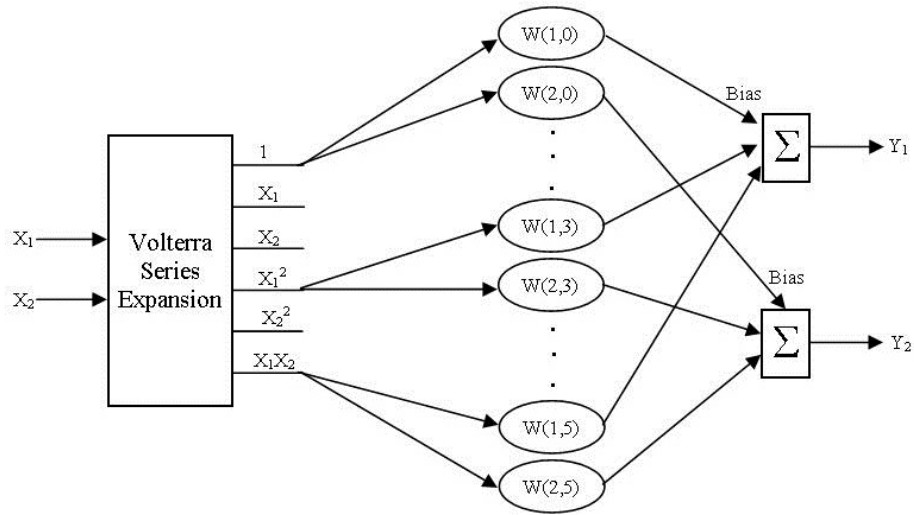


Figure 1. VNN Example

Table 1. Estimated and measured induction motor electrical parameters

Electrical Parameter	R_s (ohms)	L_s (Henry)	R_r (ohms)	σ_s (Henry) ²	L_m (Henry)
Employing VNN	0.49675	0.15364	0.17954	0.002115	0.14659
Experimentally	0.512	0.1503	0.174	0.00197	0.1437
% error 	2.9 %	2.1 %	3.1 %	6.1 %	2 %

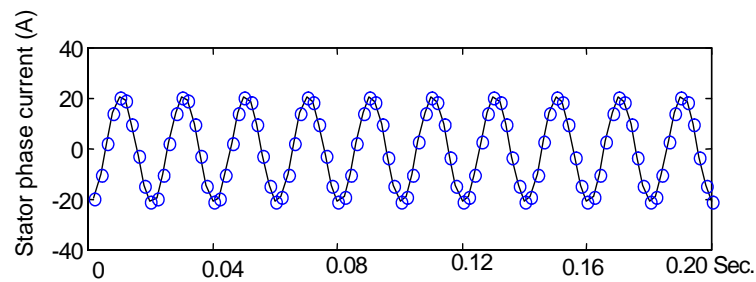


Figure 2a. Stator phase current, (—) Experimental, (o)

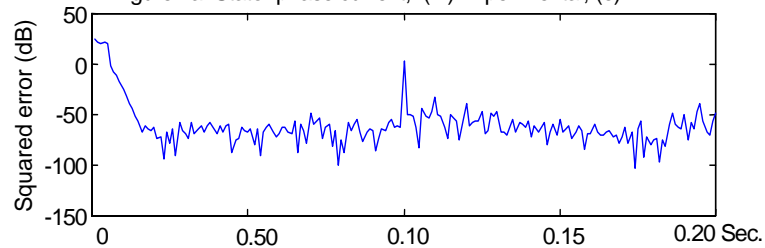


Figure 2b. Squared error between Experimental and VNN output

Figure 2. Agreement between measured and VNN estimated stator phase current

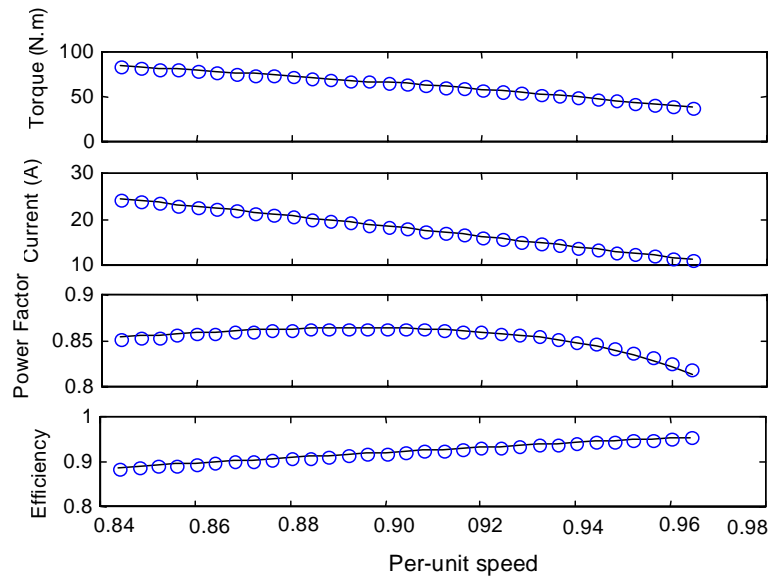


Figure 3. Measured performance criteria (--) and convergent VNN outputs (o)



Tarek I Haweel, full professor in Digital Signal Processing at Assiut University in Egypt and currently on leave at the Electrical Engineering Department at Majmaah University in Saudi Arabia. The scope of research: adaptive signal processing, neural networks, image processing, speech processing and applied mathematics. Prof. Haweel is an IEEE senior member. He received two prestigious academic awards in Egypt. He is the author of many original referenced articles.