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Regular paper

ANN Interior PM Synchronous Machine Performance Improvement Unit

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Abstract- ***This paper propose improve of the permanent magnet machine efficiency by introducing two neural network units, using the back propagation (BP) learning algorithm due to its benefits. These units will drive the motor at highly performance and optimum efficiency. The first unit using voltage reduction technique, and presents performance improvement with maximum torque per ampere control technique. The second in the manner of V \ f control, at various frequencies values. For each one of them, the goal is to pick the peaks of efficiencies at various torque values. For second one, it can be generate set of curves which govern the operation of optimum efficiency by giving suitable voltage at each frequency value. Also, deduction for one function connects between input and output for neural network, to can use with each static and dynamic model to improve its performance. The validity of these units comes from comparisons between techniques values obtained in MATLAB environment with corresponding from Neural Networks.***

Keywords: Permanent Magnet, Synchronous motor, Control, Neural Network, and MATLAB.

1. INTRODUCTION

PERMANENT Magnet Synchronous Machines (PMSMs) are widely applied in renewable energy especially in wind energy as a green or clean one, co-generation system, electrical vehicle [1-3], industrial and robotic applications due to their high efficiency, low inertia and high torque – to – volume ratio. Using of ANN (Artificial Neural Network) in the field of electric machines especially with PM Synchronous Machine (PMSM) is not strange, like in the followed examples. Distinct advantages of the PMSM include low torque ripple, self-commutation over a wider speed range, more efficient use of the volume of the machine and the ease with which it can be controlled [4]. But, there are some difficulties when operating with them, to overcome these difficulties, the artificial neural network (ANN) techniques of learning and control provide a natural framework for the design of online controllers for drive systems having unknown or uncertain dynamics [6]. The ability of the ANN to approximate nonlinear functions is the most significant. With the potential to shorten and generalize the model identification task and control scheme configuration, neural networks are extensively exploited in many control applications. Nowadays, in the ANN based control area, many researchers have been trying to develop efficient on-line adaptive learning algorithms for real-time implementation [5, 6-13]. Among them, Dynamic back-propagation (DBP) has gained a great attention [14], in which the neural network error gradient is evaluated on-line. In order to evaluate the gradient, with respect to the system output error between desired output and actual output, an identifier network has also been developed besides the controller network in most of the references. This scheme

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successfully utilizes back propagation of the system output error for the gradient evaluation, and extends the traditional static BP to a dynamic learning method in performing real-time identification and control. So, this paper aims to improve the machine efficiency by introducing two neural network units, using the back propagation (BP) learning algorithm due to its benefits. These units will drive the motor at highly performance and optimum efficiency. The first unit using voltage reduction technique, and presents performance improvement with maximum torque per ampere control technique. The second in the manner of V \ f control, at various frequencies values. For each one of them, the goal is to pick the peaks of efficiencies at various torque values. For second one, it can be generate set of curves which govern the operation of optimum efficiency by giving suitable voltage at each frequency value. Also, deduction for one function connects between input and output for neural network, to can use with each static and dynamic model to improve its performance.

2. PMSM MATHEMATICAL MODEL

The permanent – magnet excitation can be modeled as a constant current source, i_{fr}. The rotor flux is along the d axis, so the d axis rotor current is i_{fr}. The q axis current in the rotor is zero, because there is no flux along this axis in the rotor, by assumption. Then the flux linkages are written as:

$\lambda_q = L_q\, i_q$

$\lambda_d = L_d\, i_d + L_m\, i_{fr},\ \lambda_{af} = L_m\, i_{fr}$ (1)

L_m is the mutual inductance between the stator winding and rotor magnets.

The steady state equations could be obtained as follow:

$V_q = r_q\, I_q + \omega_r\, L_d\, I_d + \omega_r\, \lambda_{af}$

$V_q = r_q\, I_q + 2\pi\, f\, L_d\, I_d + 2\pi\, f\, \lambda_{af}$

$V_q = r_q\, I_q + X_d\, I_d + E_{af}$ (2)

$V_d = r_d\, I_d - \omega_r\, L_q\, I_q$

$V_d = r_d\, I_d - 2\pi\, f\, L_q\, I_q$

$V_d = r_d\, I_d - X_q\, I_q$ (3)

X_d and X_q are d and q axis reactances.

E_{af} is the generated back emf due to λ_{af}.

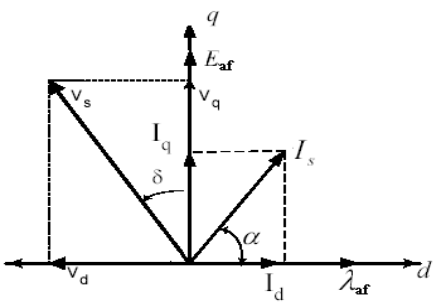

Figure 1 Phasor diagram of the PM synchronous machine.

Figure 1, summarizes some of steady state characteristics, in which: δ : Load angle.

α : Torque angle.

Steady state characteristics would be given as the following:

$V_q = V_s \cos\delta.$

$V_d = -V_s \sin\delta.$ (4)

V_d and V_q are d and q axis stator voltages.

$I_q = (V_q / R_s - C_2 (\lambda_{af} +(L_d / R_s) V_d)) / C_3.$ (5)
$I_d = V_d / R_s + C_2 L_q I_q$ (6)
$C_2 = (\omega_r / R_s).$
$C_3 = (1 + C_2^2 L_q L_d).$
I_d and I_q are d and q axis stator currents (neglect core loss).

$I_s = (I_q^2 + I_d^2)^{1/2}.$ (7)
I_s : Stator current.

$\alpha = \tan^{-1}(I_q / I_d)$ (8)
α : Torque angle

The Electromagnetic Torque T_e
$T_e = (3 / 2) (P/ 2) (\lambda_d \; I_q - \lambda_q \; I_d)$
$T_e = (3 / 2) (P / 2) (\lambda_{af} \; I_q + (L_d - L_q) I_d I_q).$ (9)

The core loss, stray loss …etc are negligible, and the copper loss P_{cu}
$P_{cu} = (3 / 2) R_s (I_q^2 + I_d^2)^{1/2}.$ (10)

P_{in} , P_{out} are the input and output power.
$P_{in} = (3 / 2) (V_d I_d + V_q I_q).$ (11)
$P_{out} = P_{in} - P_{cu}.$ (12)
The efficiency $\eta = P_{out} / P_{in}.$ (13)
Power factor (p.f) = $\cos (90° + \delta - \alpha)$ (14)

3. PMSM CHARACTERISTICS AT REDUCED VOLTAGES

Using all the previous equations in section 2, when reducing the voltage to show the effect of reducing voltage on various characteristics, especially the efficiency, to give comparisons between it at rated voltage with other residual reduced voltages.

These figures are for a PMSM which, its rated values and parameters are the following:
2.2 kW, 370 V, 4.3 A, 75 Hz, 1500 r/min, 14.0 Nm, Number of pole pairs = 3, Stator resistance R_s = 4.10, Direct axis inductance 0.036 H, Quadrature axis inductance 0.051 H.

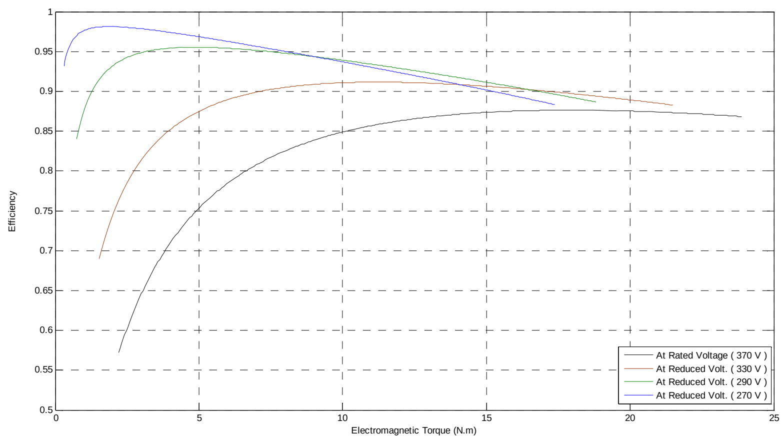

Figure 2 Efficiency and Electromagnetic Torque relation at Rated and Reduced Voltages

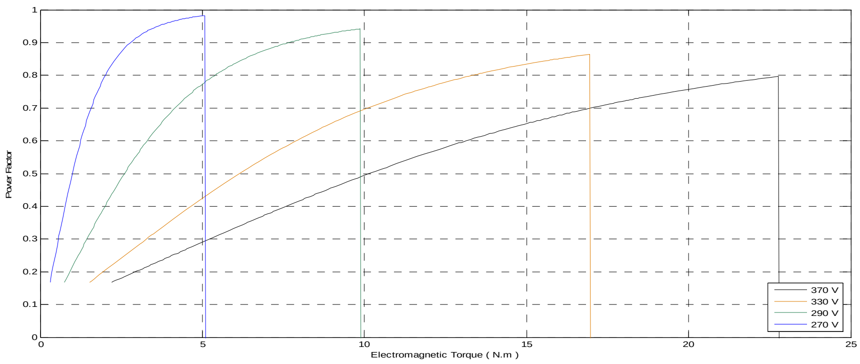

Figure 3 Power factor and Electromagnetic Torque relation at Rated and Reduced Voltages

These above figures show that, when the voltage decreases less than the rated on the performance could be improved, especially the efficiency and power factor, and so every characteristics as it will be shown next. After examining some PMSM control technique, it is found that, maximum torque per ampere technique is a suitable choice for improving the performance, especially the efficiency and so other residual characteristics also improved clearly.

4. PMSM MAXIMUM TORQUE PER AMPERE

This section introduces the maximum torque per ampere technique, with comparisons for all important PMSM characteristics, between these at max. torque per ampere, with the corresponding ones at reduced voltages, as shown before, to illustrate the validity of this choice. The torque angle (α_{MTA}) equation as presented by R. Krishnan [16], is considered here as a base for generating other characteristics equations.

$$\alpha_{MTA} = \cos^{-1} ((- 1 / (4 a I_s)) - ((1 / (4 a I_s))^2 + 0.5)^{1/2}) \quad (15)$$
$$a = L_d - L_q$$

$$I_d = I_s \cos (\alpha_{MTA})$$
$$I_q = I_s \sin (\alpha_{MTA}) \quad (16)$$

$$v_q = R_s I_q + \omega_r \lambda_{af} + \omega_r L_d I_d$$
$$v_d = R_s I_d - \omega_r L_q I_q$$
$$V_s = (v_q^2 + v_d^2)^{½} \quad (17)$$

The last equation is the more important relation, which give the required voltage to drive the machine at maximum torque per ampere, and will be considered later in this research with the torque as training or learning data for the neural network unit proposed.

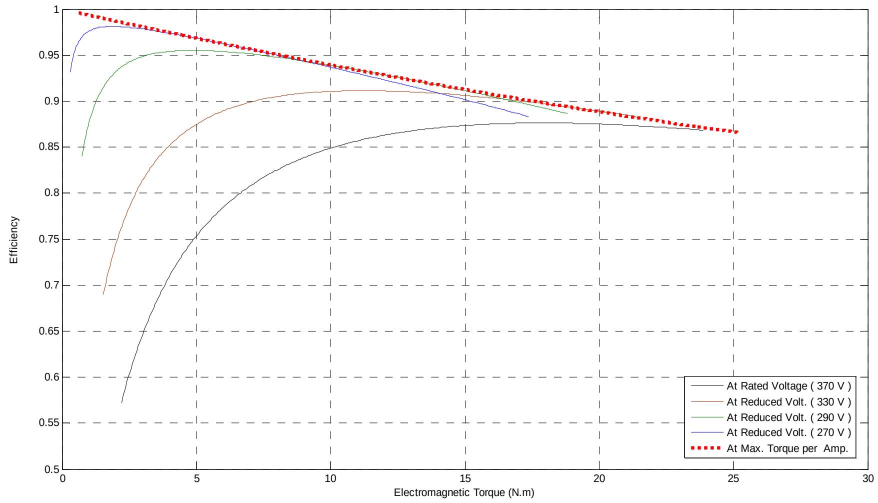

Figure 4 Efficiency at Max. Torque per Amp. with Reduced Voltages

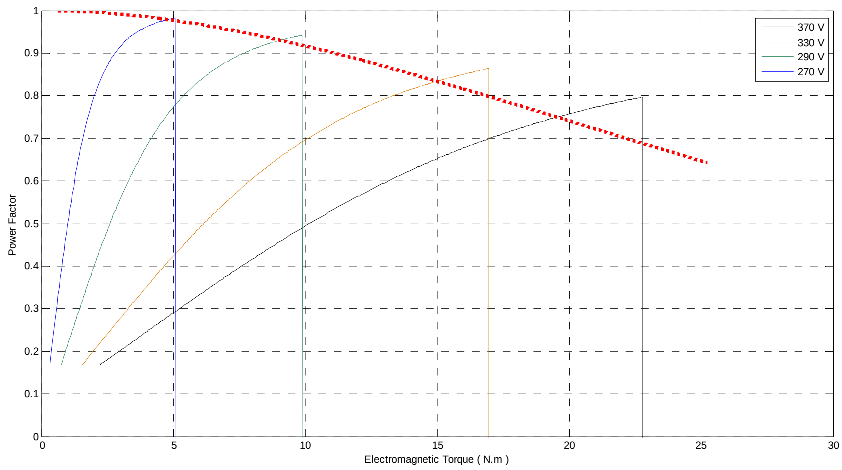

Figure 5 Power Factor at Max. Torque per Amp. with Reduced Voltages

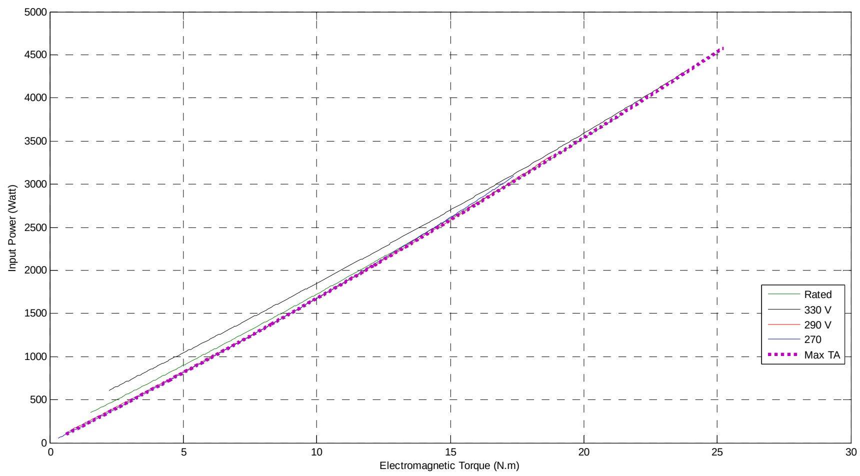

Figure 6 Input Power at Max. Torque per Amp. with Reduced Voltages

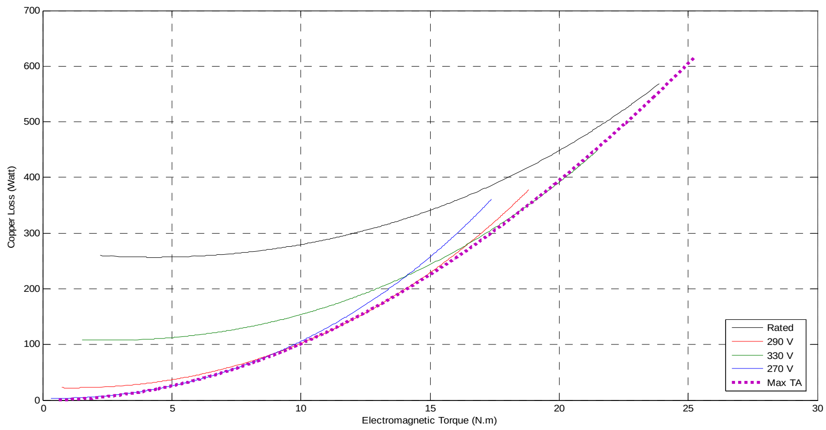

Figure 7 Copper Loss at Max. Torque per Amp. with Reduced Voltages

It is clear from the previous figures (4:7), how this technique can affect in positive manner on the various PMSM characteristics. This is notified in fig. 4 for efficiency that the dotted line for Max. T per Amp. Can pick the peaks for all efficiencies values at every reduced voltage. Also, for power factor, it is observable improvement for it. Furthermore, in fig. 6 and in fig. 7 the dotted lines for input power and copper loss respectively, have the lower values than other comparable ones.

So, to drive this machine at the improved performance, relation (17) is used to draw fig. 8, between required Max. Torque per Ampere driving voltage with electromagnetic torque at base frequency.

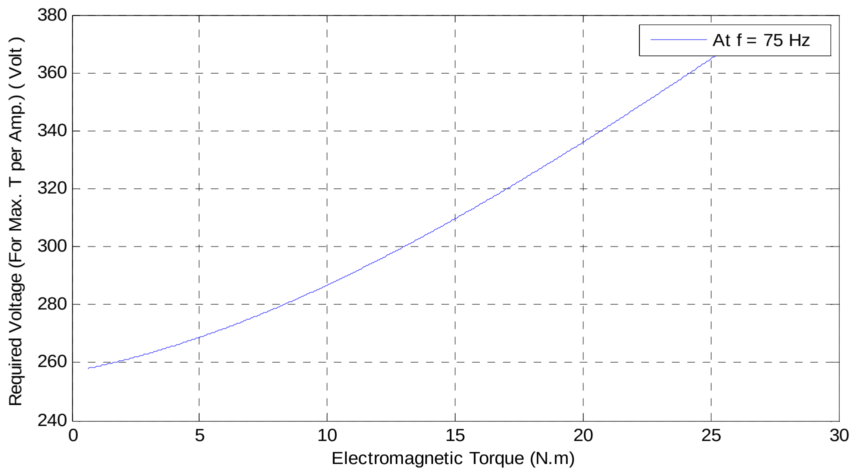

Figure 8 Required driving Voltage at Max. T/A with Electromagnetic Torque

The more general relations for any frequencies values under base frequency are presented in figure 9, these relations are the base for the second more general neural network in paper.

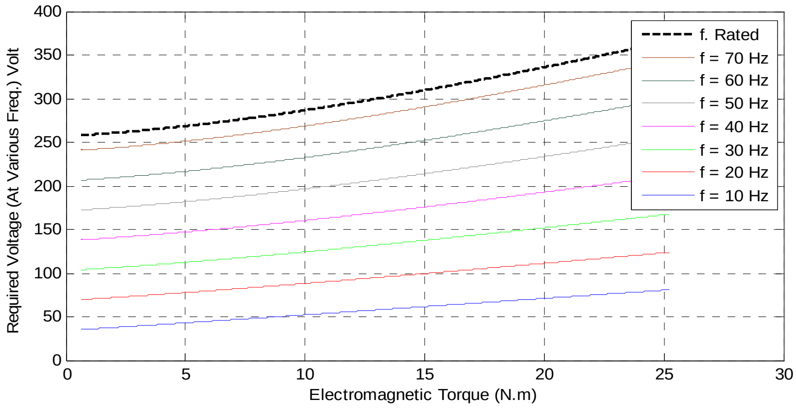

Figure 9 Required driving Voltage at Max. T/A with Elect. Torque for variable frequency

5. ANN MODELS WITH SIMULATION RESULTS

Using the Artificiel Neural Networks technique [17-29], to implement two neural network units, the first one represents the relation in fig. 8, between the electromagnetic torque as input, and required voltage to drive the machine at maximum torque per ampere as output or target as shown in fig. 10. The second one is the more generalized one because it works also, to give the required voltage to drive the motor at improved performance, at any frequency values under base frequency as shown in fig. 13. This model represents the relations in fig. 9, to make benefits from the interpolation ability of neural network, between any training values and other, also it is not faraway the truth, if it is said also this unit is capable to predict the values in between the curves for voltages at variable frequencies each other. Each one of these models has a proper number of layers with proper number of neurons as in fig. 10, fig. 13 in brief.

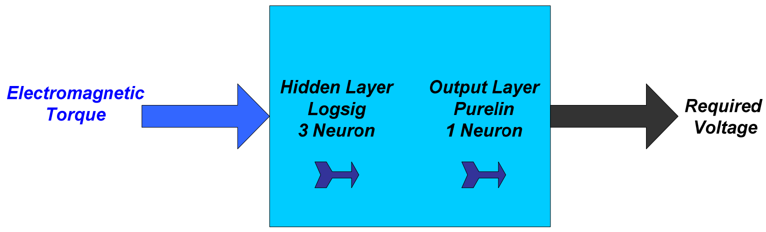

Figure 10 1st Artificial Neural Network Model

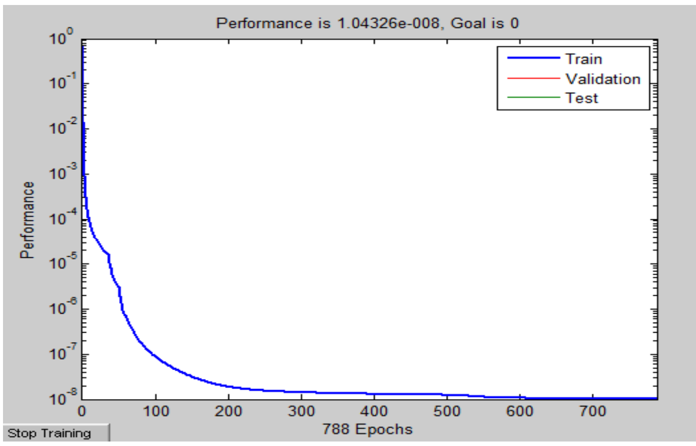

Figure 11 Training result for 1st Neural Model

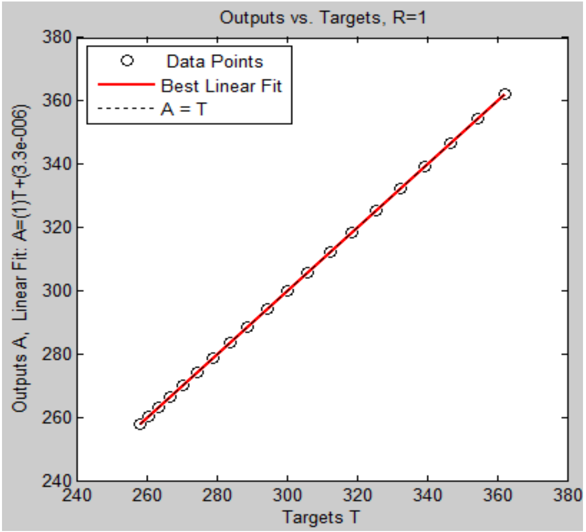

Figure 12 Comparison of actual and ANN-predicted values for Voltage (from training)

Figure 13, shows the 2nd Neural Network model, on the basis of the relations introduced in fig. 9, between the torque and voltage at any frequencies values under base one. This done with suitable no of layers with each one contains the suitable number of neurons.

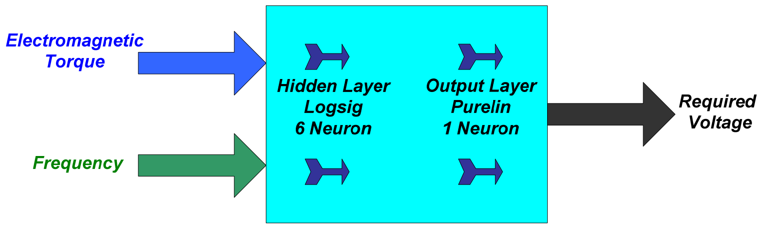

Figure 13 2nd Artificial Neural Network Model

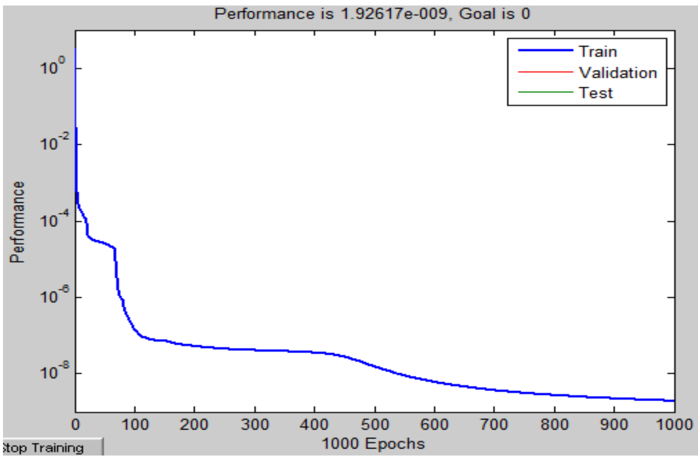

Figure 14 Training result for 2nd Neural Model

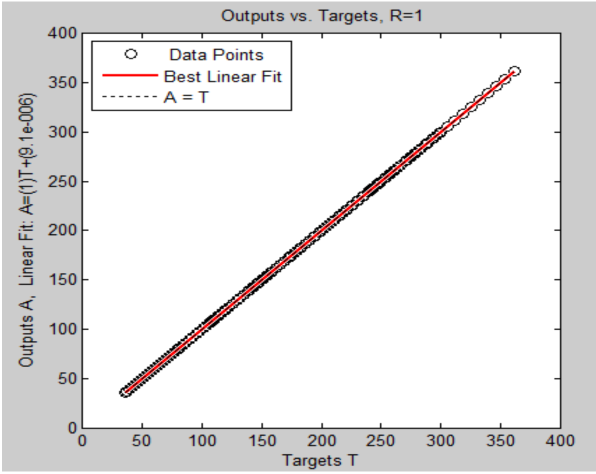

Figure 15 Comparison of actual and ANN-predicted values for Voltage (from training)

Now the more general equation for the 2nd neural network using the normalized inputs derived as shown below.

te = (Te - 12.4412) / 7.2786 (18)
f = (F - 44.3750) / 22.0687 (19)

Equations (18), (19) present the normalized inputs for electromagnetic torque and frequency, and the following equations lead to the required derived equation.

E1 = 0.8576 te + 0.5424 f - 0.8613
F1=1 / (1 + exp (- E1)) (20)
E2 = - 0.5440 te - 0.6444 f + 2.7873
F2=1 / (1 + exp (-E2)) (21)
E3 = 0.0525 te - 0.2718 f - 0.4174
F3=1 / (1 + exp (- E3)) (22)
E4 = - 0.3895 te - 0.3365 f - 0.1289
F4=1 / (1 + exp (- E4)) (23)
E5 = 0.7089 te + 1.5367 f - 0.1819
F5=1 / (1 + exp (- E5)) (24)
E6 = - 1.8334 te + 0.7567 f - 5.0098
F6=1 / (1 + exp (- E6)) (25)

vs = yi = 0.2962 F1- 2.8681 F2- 16.7974 F3- 3.5478 F4+ 0.0336 F5+ 0.1757 F6+ 10.9005 (26)

For un- normalized the out put

Vs = 86.6150 yi + 186.2211 (27)

Finally, the important comparison between two sets of curves for actual, and from the equation deduced from ANN (equation (27)) is introduced in figure 16.

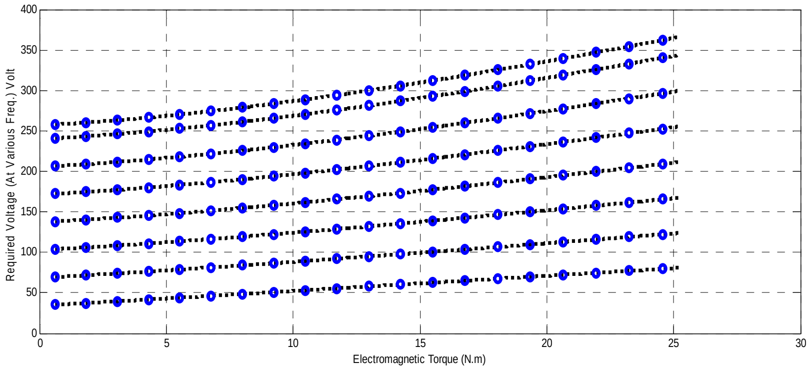

Figure 16 Comparison of actual and predicted values for the derived equation.

This deduced function from ANN could be used as a control unit to drive the dynamic model [15] for the same authors at improved performance. This function can be used directly without training ANN for each time as usual and used before.

6. CONCLUSIONS

This paper aims to improve the PM synchronous machine efficiency. This improvement done by introducing two neural network units with proper number of layers and neurons, using the back propagation (BP) learning algorithm due to its benefits. These units drive the motor at notified high performance, it is clear especially in efficiency, power factor, input power, and losses. The first unit using voltage reduction technique, and presents performance improvement with maximum torque per ampere control technique. The second operates at various frequencies values under the base frequency, to give the required suitable voltage for maximum torque per ampere operation. For each one of them, the goal is to pick the peaks of efficiencies at various torque values. For second one, it can be generate set of curves which govern the operation of optimum efficiency by giving suitable voltage at each frequency value. Also, deduction for one function connects between input and output for neural network, to can use with each static and dynamic model to improve its performance. By using this ANN equation derivation technique, there is no need to train the neural network every time, when wanting to operate this unit, but instead of this, the derived equation could be used directly. The validity of these units comes from comparisons between techniques values obtained in MATLAB environment with corresponding from Neural Networks.

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