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Development of Artificial Neural Network based Speed and Torque Prediction Models of a DC Shunt Motor

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***Abstract* — DC motor models are widely used to predict speed and torque and also in various speed control applications. The statistical modeling approach is based on curve fitting using regression and exhibits poor accuracy when the range of control factors is too large or the input-output relation is highly complex and non-linear. This work aims to predict speed and torque of a DC shunt motor, given the external armature resistance, the field current and the armature current, by developing Artificial Neural Network (ANN) based models. Feed-forward ANN architecture, trained using Error back propagation training algorithm (EBPTA) is selected for modeling purpose. The input-output patterns required for ANN training and testing are obtained by conducting experiments on a DC shunt motor with inputs such as armature current, field current and external armature resistance. The experiments are conducted as per Full Factorial Design (FFD) of Design of Experiments (DOE) concept. A generalized C program is developed to train and test the selected ANN.**

Index Terms—**Artificial neural network (ANN), DC motor modeling, error back propagation training algorithm (EBPTA), full factorial design (FFD) of design of experiments (DOE).**

I. Introduction

Mathematical modeling is used to establish a relationship between the response and important design factors of a system or a process. The response of a system can be defined as the quality characteristic of that process. Ex: cost, efficiency, output power, torque, speed and so on where as the design factors are the variables of the system or process that govern the response value. Ex: current, voltage, size of a part, slip, power factor, firing angle etc. Using the model it is possible to analyze the response, optimize the process, set the control factor values to get required performance.

There are numerous modeling approaches available, which are well documented in the open literature. Most methods like empirical modeling and response surface methodology (RSM) are based on statistical modeling. The statistical modeling approach is based on curve fitting using regression and exhibits poor accuracy when the range of control factors is too large or the input-output relation is highly complex and non-linear [1,2]. These constraints have led to the development of models based on artificial neural network (ANN).

The objective of artificial neural network (ANN) development is to imitate human brain so as to implement the functions such as association, self-organization, and generalization. Neuro-computing is concerned with parallel, distributed and adaptive information processing systems.

The advantage of using ANN based models is that it can capture any non-linear and complex input–output relationships [1,2] and also they are faster and accurate than other methods because of their parallel structure. In the recent years, ANN is applied in various fields like: Modeling of manufacturing processes [3], System/Apparatus condition monitoring [4] and Power system monitoring and control applications [5].

II. ANN Modeling

The generic feed forward network is characterized by the lack of feedback. This type of network can be connected in series or in cascade to create a multilayer network. In such a network, the output of a layer is input to the following layer. A multilayer network is illustrated in Fig.1.

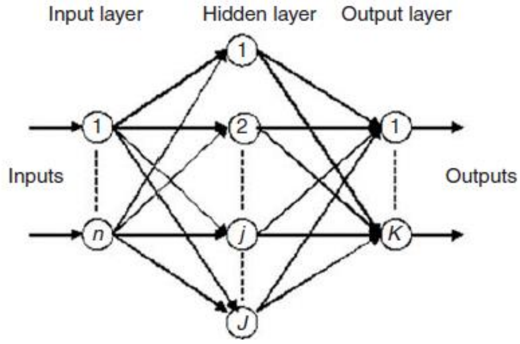

Fig. 1: A Multilayer feed forward network [6]

A. Generalized Delta Learning Rule

In this section, the delta rule is generalized to update weights of links connected to neurons in any layer [7].

* Net input to output neuron k,

$$net_k = w_{kj}\, y_j \tag{1}$$

* Output of output layer neuron,

$$o_k = f(net_k) = \frac{1}{1+ e^{(-net_k)}} \tag{2}$$

* Squared error,

$$E = \frac{1}{2}(d_k - o_k)^2 \tag{3}$$

* Error term for output layer neuron,

$$\delta_k = (d_k - o_k)\, f^{'}(net_k) \tag{4}$$

where d_k is the desired output

* Change in weight of link connecting output neuron to hidden neuron,

$$\Delta w_{kj} = \eta \delta_k y_j \tag{5}$$

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* Change in weight of link connecting hidden to input neuron,

$$\Delta v_{ji} = -\eta \frac{\partial E}{\partial v_{ji}} \quad (6)$$

B. Error Back Propagation Training Algorithm (EBPTA)

The back propagation of error (dk - ok) using the negative gradient descent technique is divided into functional steps such as calculation of error signals and weight adjustments between different layers [8].

- Error signal of output layer neuron i

Unipolar

$$(da)_i = [(yt)_i - (yo)_i]\,(yo)_i\,[1-(yo)_i] \quad i = 1, 2\ldots no \quad (7)$$

Bipolar

$$(da)_i = 0.5\,[(yt)_i - (yo)_i]\,[1-(yo)_i^2] \quad i = 1,2\ldots no \quad (8)$$

- Error signal of neuron i in second hidden layer

Unipolar

$$(dh2)_i = (yh2)_i\,[1-(yh2)_i]\sum_{j=1}^{no}(da)_j(woh)_{ij} \quad i = 1,2\ldots nh2 \quad (9)$$

Bipolar

$$(dh2)_i = 0.5\,[1-(yh2)_i^2]\sum_{j=1}^{no}(da)_j(woh)_{ij} \quad i = 1,2\ldots nh2 \quad (10)$$

- Error signal of neuron i in first hidden layer

Unipolar

$$(dh1)_i = (yh1)_i\,[1-(yh1)_i]\sum_{j=1}^{nh2}(whh)_{ij}(dh2)_j \quad i = 1,2\ldots nh1 \quad (11)$$

Bipolar

$$(dh1)_i = 0.5\,[1-(yh1)_i^2]\sum_{j=1}^{nh2}(whh)_{ij}(dh2)_j \quad i = 1,2\ldots nh1 \quad (12)$$

The weight adjustments are as follows:

- Between i^{th} output neuron and j^{th} neuron in second hidden layer

$$(\Delta woh)_{ij}^{(n+1)} = \eta\,(da)_i\,(yh2)_j + \alpha\,(\Delta woh)_{ij}^{n} \quad (13)$$

$$(\Delta woh)_{ij}^{n+1} = (woh)_{ij}^{n} + (\Delta woh)_{ij}^{(n+1)} \quad (14)$$

- Between i^{th} neuron in second hidden layer and j^{th} neuron in first hidden layer

$$(\Delta whh)_{ij}^{(n+1)} = \eta\,(dh2)_i\,(yh1)_j + \alpha\,(\Delta whh)_{ij}^{n} \quad (15)$$

$$(\Delta whh)_{ij}^{n+1} = (whh)_{ij}^{n} + (\Delta whh)_{ij}^{(n+1)} \quad (16)$$

- Between i^{th} neuron in first hidden layer and j^{th} neuron in input layer

$$(\Delta whi)_{ij}^{(n+1)} = \eta\,(dh1)_i\,(yi)_j + \alpha\,(\Delta whi)_{ij}^{n} \quad (17)$$

$$(\Delta whi)_{ij}^{n+1} = (whi)_{ij}^{n} + (\Delta whi)_{ij}^{(n+1)} \quad (18)$$

where η = Learning factor and α = momentum constant.

The steps involved in the ANN training process are given below [9]:

Step 1: Initialize all the weights to small random values.

Step 2: Present the input-desired output patterns one by one, updating the weights each time.

Step 3: When all the patterns are presented, compute the mean square error (MSE) due to all outputs and NP number of patterns as:

$$MSE = \frac{1}{NP}\sum_{P=1}^{NP}\sum_{K=1}^{K}(d_{kp} - o_{kp})^2$$

Step 4: If (MSE < Specified tolerance)
Then stop. Else, go to Step 2.

III. Experimental Details

Supervised learning of ANN requires examples of input – desired output known as “training set” or “training patterns”. The input – output patterns required for ANN training and testing are obtained by conducting experiments on a DC shunt motor with inputs such as armature current, field current and external armature resistance. Experiments were performed on DC shunt motor with specifications: 3.7 kW, 220 V, 20 A, 1450 rpm.

Fig. 2 shows the process diagram. The control factors are external armature resistance (Rext), field current (If) and armature current (Ia). The speed (N) and torque (T) are considered as the responses. The corresponding circuit diagram is shown in Fig. 3.

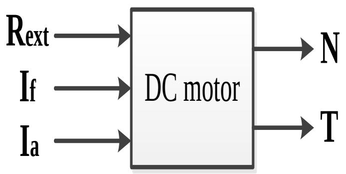

Fig. 2: Process Diagram

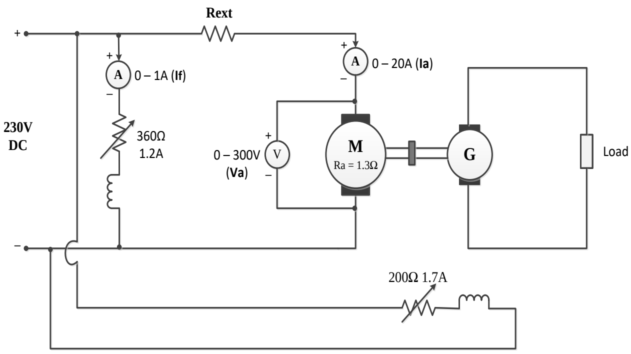

Fig. 3: Experimental setup

Three levels are defined each for external armature resistance (Rext) and field current (If) and five levels for armature current (Ia) as listed in table 1. Thus 45 experiments were performed.

Table 1: Levels defined for control factors

	Level 1	Level 2	Level 3	Level 4	Level 5
Rext (Ω)	9	12	15	-	-
If (A)	0.3	0.4	0.5	-	-
Ia (A)	2	4	6	8	10

Experiments are conducted as per full factorial design (FFD). For each combination of the factor levels, the speed (N) was measured and torque (T) was determined. The torque was calculated as follows:

No load test was conducted to determine the rotational losses,

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Va = 214 V; Ia = 0.9 A; Ra = 1.3 Ω

* Rotational losses,

$$P_{rot} = \frac{V_a I_a - I_a^2 R_a}{2} = 95.77\ W$$

The shaft torque is calculated as under:

* Armature power input,

$$P_{in} = V_a * I_a$$

* Shaft power output,

$$P_{shaft} = P_{in} - I_a^2 R_a - P_{rot}$$

$$P_{shaft} = \frac{2\pi N T}{60} \Rightarrow T = \frac{60 P_{shaft}}{2\pi N}$$

* Torque,

$$T = \frac{60\,(V_a I_a - I_a^2 R_a - 95.77)}{2\pi N}$$

The 45 input – output patterns, thus obtained are tabulated in table 2. In order to validate / test the trained ANN, new verification experiments with random levels of control factors within the selected range were performed. 32 experiments were conducted. The input – output patterns, thus obtained are tabulated in table 3.

Table 2: Summary of input – output patterns for training

Rext (Ω)	If (A)	Ia (A)	N (rpm)	T (Nm)
9	0.3	2.3	1563	1.98
9	0.3	4	1425	3.77
9	0.3	6	1239	5.83
9	0.3	8	1069	7.69
9	0.3	10	903	9.45
9	0.4	2	1414	1.99
9	0.4	4	1258	4.51
9	0.4	6	1120	6.96
9	0.4	8	970	9.26
9	0.4	10	828	11.46
9	0.5	2	1318	2.13
9	0.5	4	1173	4.91
9	0.5	6	1033	7.55
9	0.5	8	895	10.04
9	0.5	10	757	12.28
12	0.3	2	1556	1.66
12	0.3	4	1355	3.80
12	0.3	6	1147	5.80
12	0.3	8	936	7.64
12	0.3	10	732	9.05
12	0.4	2	1355	1.90
12	0.4	4	1172	4.32
12	0.4	6	986	6.63
12	0.4	8	805	8.88
12	0.4	10	621	10.67
12	0.5	2	1295	2.08
12	0.5	4	1125	4.78
12	0.5	6	961	7.40
12	0.5	8	791	9.81
12	0.5	10	631	12.01
15	0.3	2.2	1454	1.78
15	0.3	4	1232	3.62
15	0.3	6	971	5.55
15	0.3	8	699	7.17
15	0.3	10	442	7.65
15	0.4	2	1278	1.84
15	0.4	4	1043	4.20
15	0.4	6	838	6.44
15	0.4	8	596	8.15
15	0.4	9.8	391	8.97
15	0.5	2	1285	2.13
15	0.5	4	1078	4.77
15	0.5	6	882	7.42
15	0.5	8	668	9.79
15	0.5	10	476	11.51

Table 3: Summary of input – output patterns for testing

Rext (Ω)	If (A)	Ia (A)	N (rpm)	T (Nm)
9	0.32	2.8	1576	2.68
9	0.32	3.9	1490	3.90
9	0.32	6.3	1303	6.39
9	0.32	8.7	1092	8.79
9	0.32	8.1	1154	8.16
9	0.32	4.9	1424	4.93
9	0.44	2.2	1418	2.30
9	0.44	5.4	1190	6.37
9	0.44	6.5	1108	7.66
9	0.44	8.3	963	9.68
9	0.44	9.4	889	11.06
12	0.36	9.4	821	10.45
12	0.36	7.5	1007	8.21
12	0.36	6.5	1096	7.06
12	0.36	2.6	1460	2.61
12	0.46	2.3	1353	2.45
12	0.46	5.7	1064	6.84
12	0.46	7.8	896	9.44
12	0.46	9.3	758	10.96
15	0.34	9.4	615	9.28
15	0.34	7.1	907	7.27
15	0.34	4.3	1241	4.37
15	0.34	3.5	1334	3.50
15	0.43	3.1	1248	3.39
15	0.43	5.4	1003	6.23
15	0.43	6.4	898	7.39
15	0.43	8.3	673	9.38
15	0.47	8.5	632	9.71
15	0.47	7.3	769	8.64
15	0.47	6.2	874	7.34
15	0.47	3.7	1144	4.24
15	0.47	2.9	1218	3.25

IV. Analysis Of Results

A. Training Performance

A generalized C – program is developed to implement the speed and torque prediction model. The input – output patterns obtained from experimentation are used for training and testing. The mean squared error (MSE) calculated at the end of each iteration is plotted against the number of iterations. The resulting graph is used to evaluate the performance of the ANN.

After studying the effect of various factors on the ANN training, we choose the following values for the final training:

- Number of neurons in first hidden layer, nh1 = 9
- Number of neurons in second hidden layer, nh2 = 10
- Learning rate, η = 0.1
- Momentum constant, α = 0.9

Fig. 4 shows the MSE Vs Iterations graph.

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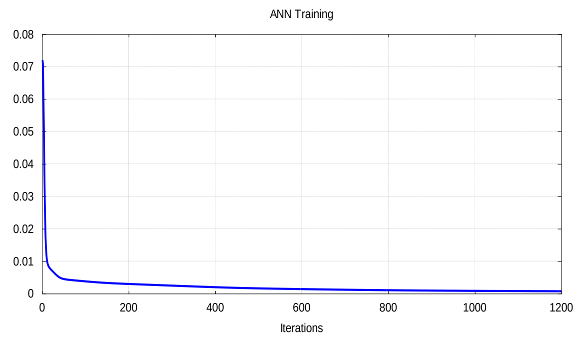

Fig. 4: Training Performance

B. *Percentage Prediction Errors*

After successful training of the ANN, it is observed that there are some errors in prediction of speed and torque values. The percentage errors in prediction for the 45 testing data are depicted in Fig. 5. The maximum prediction error in speed is 28.88% and that for torque is 27%.

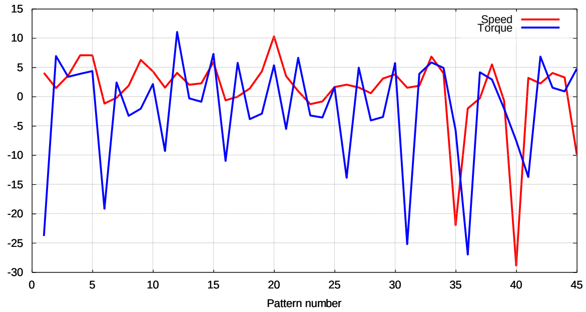

Fig. 5: Error profiles of speed and torque for training patterns

Similarly, the percentage errors in prediction of the testing patterns are depicted in Fig. 6. The maximum prediction error in speed is found to be 21% and that for torque is found to be 23%.

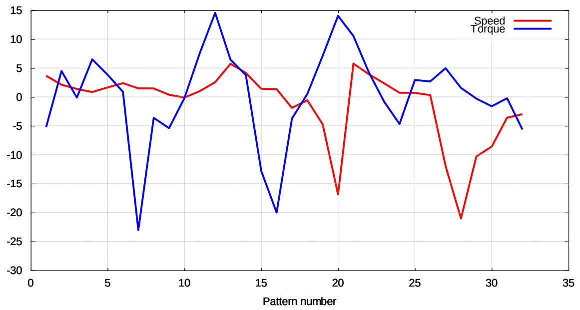

Fig. 6: Error profiles of speed and torque for testing patterns

C. *Characteristic Analysis*

In the direct effect plots, the effect of one factor is considered on the response, while the other factors are held constant. Interaction effects are not considered here.

- Speed characteristics: For a given value of field current and armature current, as the external armature resistance is increased, speed decreases. For a given value of field current and external armature resistance, as the armature current is increased, speed decreases. For a given value of external armature resistance and armature current, as the field current is increased, speed decreases. This can be observed in Fig. 7 where speed is plotted Vs Armature current, for different values of field current with external armature resistance being held constant.

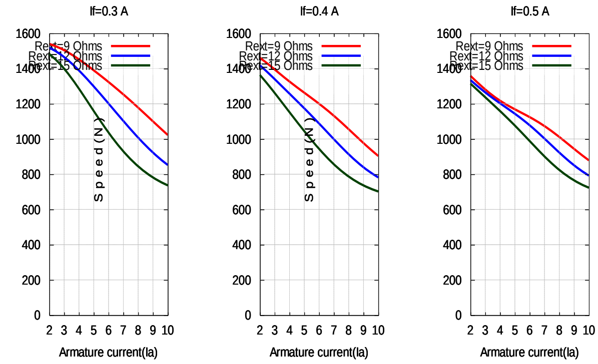

Fig. 7: Speed characteristic analysis

- Torque characteristics: For a given value of field current and armature current, as the external armature resistance is increased, torque decreases. For a given value of field current and external armature resistance, as the armature current is increased, torque increases. For a given value of external armature resistance and armature current, as the field current is increased, torque increases. This can be observed in Fig. 8 where torque is plotted Vs Armature current, for different values of field current with external armature resistance being held constant.

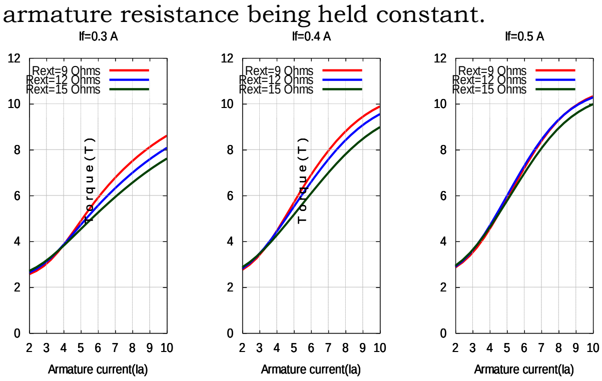

Fig. 8: Torque characteristic analysis

Conclusions

The principal objective of the work presented in this report was to develop an ANN model to predict speed and torque of a DC shunt motor with field current, armature current and external armature resistance as control factors. The multilayer feed - forward ANN architecture; trained using EBPTA was employed for this purpose. The training patterns of input-output were obtained by conducting the load tests as per FFD of experiments.

The developed ANN model was tested and validated using both training and new validating data. The investigation revealed that the ANN predicted torque and speed values are very close to that obtained from experiments.

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