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Direct Current Motor Model Using RBF

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Abstract— Direct current motors are widely utilized in industries and are very popular in performance control systems because of the encroachment and innovation they provide in power electronics. This paper aims at studying and using different types of neural networks namely; feed forward neural network, cascade forward neural network and radial basis function network to predict the future value of torque of the motor engine. The results show that radial basis function networks outperformed the feed forward and cascade feed forward networks.

Keywords— Radial Basic Function, Cascade Feed Forward Neural Networks, Feed Forward Neural Networks, DC Motor Engine.

I. INTRODUCTION

Direct current motors are the most commonly used in manufacturing and business production today. Direct motors are very popular in systems with high performance control due to the encroachment and innovation they create in power electronics. As a matter of fact, their best traits, such as torque and robot speed control, have made them extensively responsible for their widespread use or application in automation systems [1], [2] and [3].

Apparently direct current motors are broadly applied and used in many sorts of applications such as steel manufacturing, robotic systems, paper processing, automation systems, and mining industries. In general direct motors are conventionally modelled linearly in order to aid the application of linear control theory in controller designs. Nevertheless, the majority of the existing linear controllers usually do not lead to good tracking and regulation responses when the controlled system is subjected to a wide range of operating conditions [1], [2] and [3].

Artificial neural networks (ANN) have received immense interest and have developed massive credit over the last two decades due to their huge breadth of applicability at both industrially and academic levels. They have been used to solve many engineering, physical science, and medical problems, due to their outstanding weight connections and ability to learn and obtain meaning from problematical or inaccurate data; thus they can be used to mine patterns and discover trends that are not simple and straight forward to observe by either humans or other more linear computer techniques. Artificial neural computations are designed to carry out tasks such as pattern recognition, prediction and classification. The performance of this type of machine learning depends on the learning algorithm and the given application, the accuracy of the modelling, and structure of each model. The most popular type of learning algorithm for the feed forward neural network is the back propagation algorithm. The reason for selecting the feed forward neural network with back propagation learning algorithm is mainly because this network is easier than other types of network [4].

This paper explicitly and effectively examines the types of ANN to forecast torque of direct current motors. The torque of a direct current motor can be determined by prediction with given power, electrical current and speed as input variables [1], [2] and [3].

This paper is organized as follows: Section II briefly describes different types of neural networks and their main concepts. In Section III, we present learning algorithms that are used to train the different types of neural networks. In section IV, simulation and results are explained, and in the final section the conclusion is outlined.

II. TYPES OF NETWORKS

It is obvious that an artificial neural network is a very popular type of machine learning and it can be considered as another model that is based on modern mathematical concepts. Artificial neural computations are designed to carry out tasks such as pattern recognition, prediction and classification. In this paper three different types of neural networks are discussed, namely, feed forward artificial neural networks, cascade feed forward artificial neural networks, and radial basis function neural networks (RBF) [4].

A. Feed Forward Artificial Neural Networks

The basic feed forward artificial neural networks [4] as in Fig. 1 consist of three interconnection layers: one input layer, one or more hidden layers, and one output layer. The feed forward artificial neural networks allow signals to travel one way only-- from the input to the hidden layer and then to the output layer. There is no feedback; i.e. the output of any layer does not affect that same layer. The feed forward artificial neural networks tend to be straightforward networks that associate inputs with outputs. They are extensively used in pattern recognition. This type of organisation is also referred to as bottom-up or top-down.

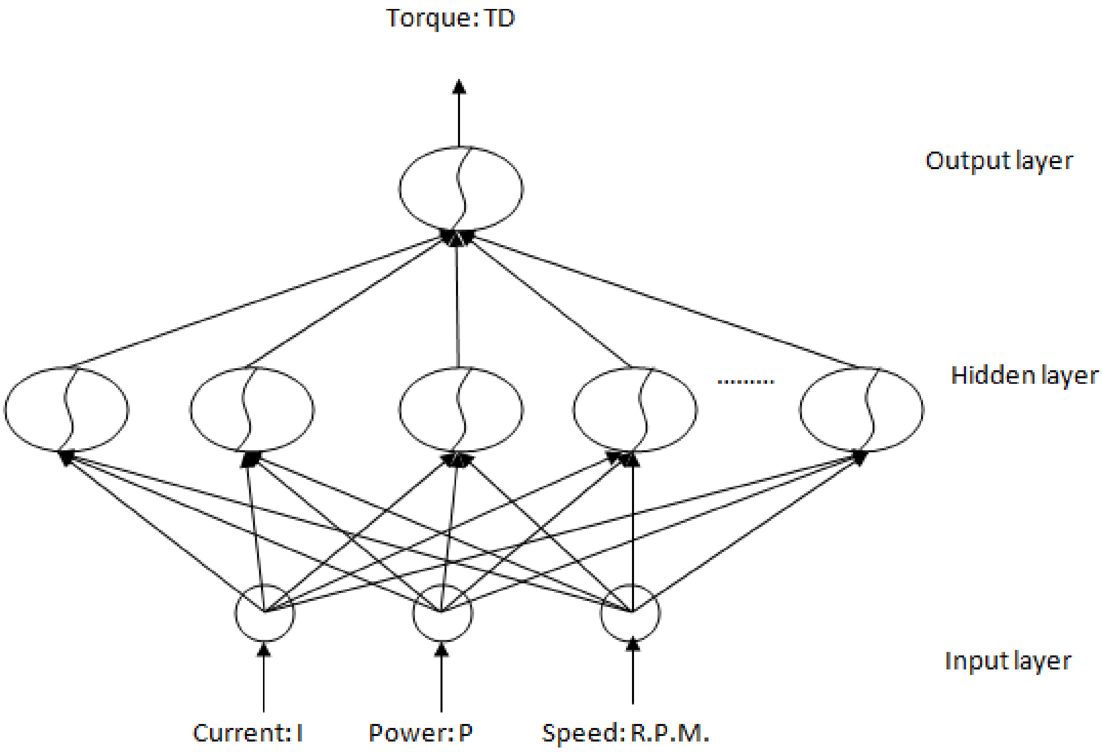

Fig 1: the above network allows signals to travel one way only; from the input to the hidden layer and then to the output layer. There is no feedback i.e. the output of any layer does not affect that same layer.

According to the connectivity of the network defined in its architecture, the output of the hidden layer can be expressed as a function of the input layer's outputs:

$$\tilde{h}_j = \sum_{i=0}^{N} I_i W_{ji} \text{ ----------- } (1)$$

i is the index of input variable and weight from i to N, W_{ji} is the weight connection from neuron i to neuron j.
The output of the jth neuron in the hidden layer is:

$$H_j = f(\tilde{h}_j) \text{ ----------- } (2)$$

Where: H_j is the output of the neuron; $f(\tilde{h}_j)$ is the activation function and normally chosen as sigmoid shape [2].

B. Cascade Feed Forward Artificial Neural Networks

Cascade feed forward artificial neural networks are another branch of traditional feed forward networks. However, these types of neural networks contain weight connections from the input layer to each layer, and from each layer to the successive layers (see Fig. 2). Although a two- layer feed forward network may possibly learn virtually any input-output relationship, it is possible that feed forward networks with more layers might learn more complex relationships faster. In this type of network an extra function will be added to the structure of the forward networks when cascading is used. For example, three layer networks have connections from layer 1 to layer 2, layer 2 to layer 3, and layer 1 to layer 3. The three layer network also has connections from the input to all three layers. The additional connections improve the speed at which the network learns the desired relationship [5, 6, 7, and 8].

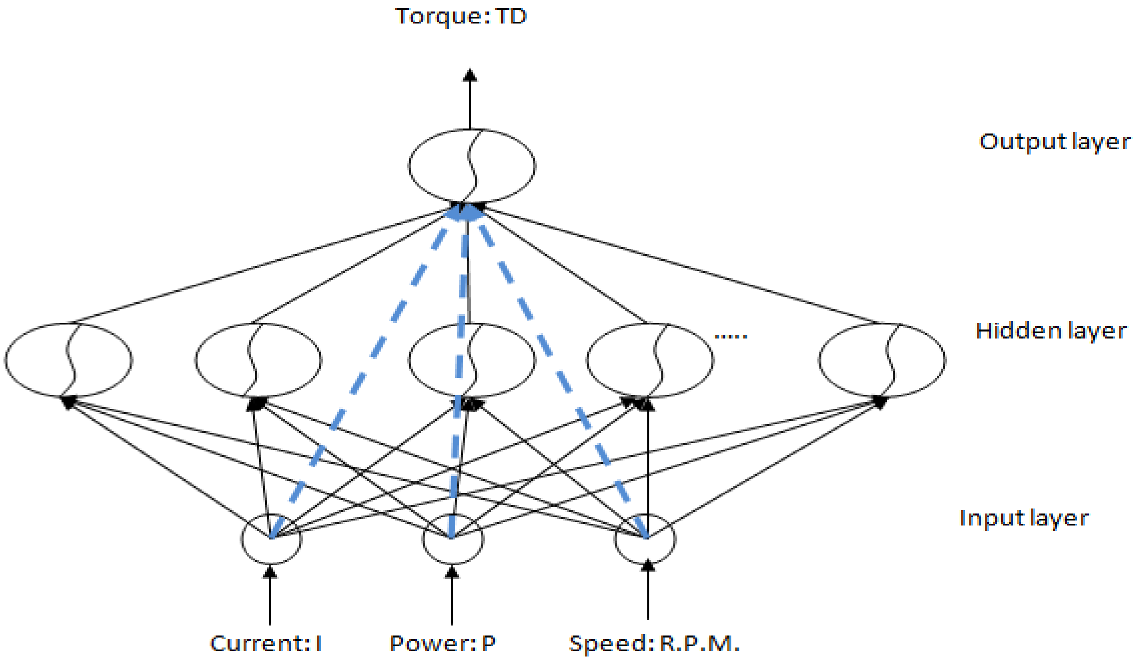

Fig. 2: shows cascade feed forward artificial neural networks: a three layer network has connections from layer 1 to layer 2, layer 2 to layer 3, and layer 1 to layer 3. The three layer network also has connections from the input to all three layers.

C. Radial Basic Function

Radial basis function is another type of neural network; this network consists of three-layers. This particular architecture is constant see Fig 3. These three layers are namely: input layer, hidden layer and output layer. It is clear that the input layer supplies the network with the input patterns. The hidden layer processes or maps the input patterns in the hope to that they can be linearly separable. The output layer creates linear separation. It is agreed that the architecture of radial basis function networks resembles the feed forward neural network since both network can have three layers [5].

A radial basis function network can be implemented using a feed forward approach via increased input dimension. The similarity between these two networks is the limited topological form of the networks. In fact, these two networks perform their own tasks in their own way very differently. As already mentioned, radial basic function networks can have only three layers, whereas the feed forward networks can have more than three layers [5].

According to the connectivity of the network defined in its architecture, the output of the hidden layer can be expressed as a function of the input layers outputs:

$$\tilde{h}_j = [I_1 W_{j1}, I_2 W_{j2}, I_3 W_{j3} ......I_i W_{ji} ....I_N W_{jN}] ....(3)$$

i is the index of input, j is the index of hidden and $I_i W_{ji}$ is the weight connection between i th input and jth hidden. The output of the hidden neuron can be computed as follows:

$$\varphi(\tilde{h}_j) = \exp\left(\frac{\left\| \tilde{h}_j - c_j \right\|^2}{\sigma_j} \right) ....(4)$$

Where the activation function $\varphi(\tilde{h}_j)$ for hidden neuron j is normally chosen as Gaussian function; c is the centre of hidden neuron j and σ is the width of hidden unit j. c is a centre matrix and width vector σ; in general, the input weights are all set to 1. The simple linear least squares (LS) method can only adjust the output weights and it performs for nonlinear cases. Iteratively, the LS method [5, 6, 7, 8, and 9] develops the nonlinear performance of output layer.

The output neuron can be computed as follows:

$$\tilde{o}_k = \sum_{k=0}^{K} \varphi(\tilde{h}_j) W_{kj} ----------(5)$$

Where: k is the index of output; W_{kj} is the output weight between hidden neuron j and output neuron k;
The output of the kth neuron in the output layer is:

$$O_k = f(\tilde{o}_k) \quad ----------(6)$$

Where: O_k is the output of the neuron; $f(\tilde{o}_k)$ is the activation function and normally chosen as sigmoid shape.

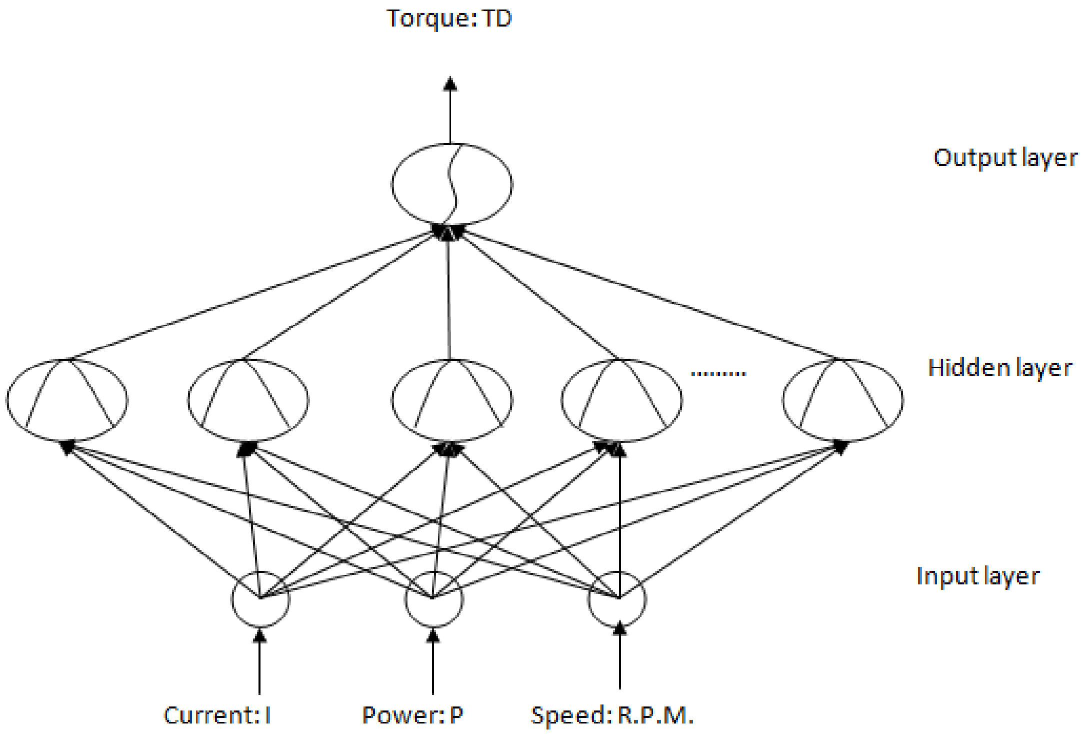

Fig 3: shows radial basis function neural network with the Gaussian function in the hidden layer neurons.

III. LEARNING ALGORITHMS

Three types of learning algorithms are used to train all the three types of networks, namely: the back propagation algorithm, marquarder levenbregr backbropagation and orthogonal least square learning algorithm [5], [6] and [7].

The back propagation algorithm is an example of supervised learning [4]. It is based on the minimization of error by gradient descent. The network is trained with back propagation algorithm. When a target output pattern exists, the actual output pattern is calculated. The gradient descent acts to modify each weight in the layers to reduce the error between the target and actual output patterns. The modification of the weights is accumulated for all patterns and finally the weights are updated.

Both Kenneth Levenberg and Donald Marquardt purely and independently developed the levenberg–marquardt algorithm [5-12]. This algorithm introduces a numerical solution to the problem of minimizing a nonlinear function. The main aspect of this algorithm is that it is quick and converges steadily. This type of algorithm is very appropriate for training applications that are small and medium sized problems [5-12].

Radial basis function networks use a common type of learning algorithm that is based first on selecting several random data points as radial basis function canters to work out the weights of the network. Those centres which are basis functions are sampled randomly among the input instances or are obtained by the orthogonal least square learning algorithm or found by clustering the samples and choosing the cluster means as the centres. The widths of radial basic functions are usually constant to same value which is proportional to the maximum distance between the chosen centres [5-12].

IV. SIMULATION AND RESULTS

Data sets: A relatively large data set is used in this paper. 507 samples are used. The data set is divided into two parts the training and testing sets -- 406 training patterns are used to train all the three different networks. 100 training samples are used for testing the networks. All the networks are fed with identical inputs and output variables. Three input features are fed in to the networks, namely: current, power and speed. The networks have only one output to predict which the torque was. The structure of the networks is as follows:

The feed forward network structure consists of three layers: 3-6-1; three input neurons, 6 hidden neurons and 1 output neuron. The learning rate was 0.35, and the momentum rate was a constant 0.7. The network updates weight and bias values according to gradient descent with adaptive learning rate. The network is trained with 3500 training cycles.

The cascade feed forward networks structure consists of three layers: 3-6-1; three input neurons, 6 hidden neurons and 1 output neuron. The learning rate was 0.35; the levenberg–marquardt algorithm was used to train the network. The network was trained with 3500 training cycles.

The radial basis function network structure consists of three layers: 3 input neurons, the number of neurons to add between displays was 25, and the spread of radial basis functions was 400.

In fact, in this paper we have used various structures and parameters so that we can get the best results. Fig. 4 shows the predicated values that are produced from the feed forward network against the target.

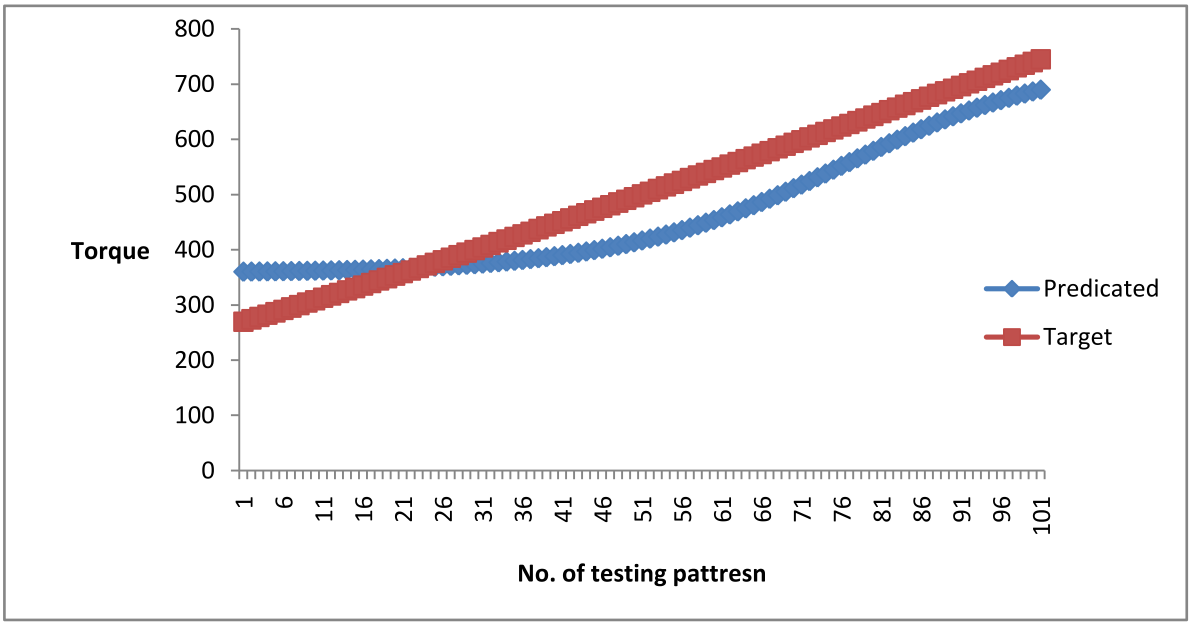

Fig. 4: shows the predicated values of the feed forward neural network against the target values.

It is clear that the results shown in Fig 5 are more accurate than those produced in Fig. 4. This means that the cascade feed forward is more accurately predicted the actual values compared to feed forward neural network. This is due to the differences in the learning algorithms and the structures.

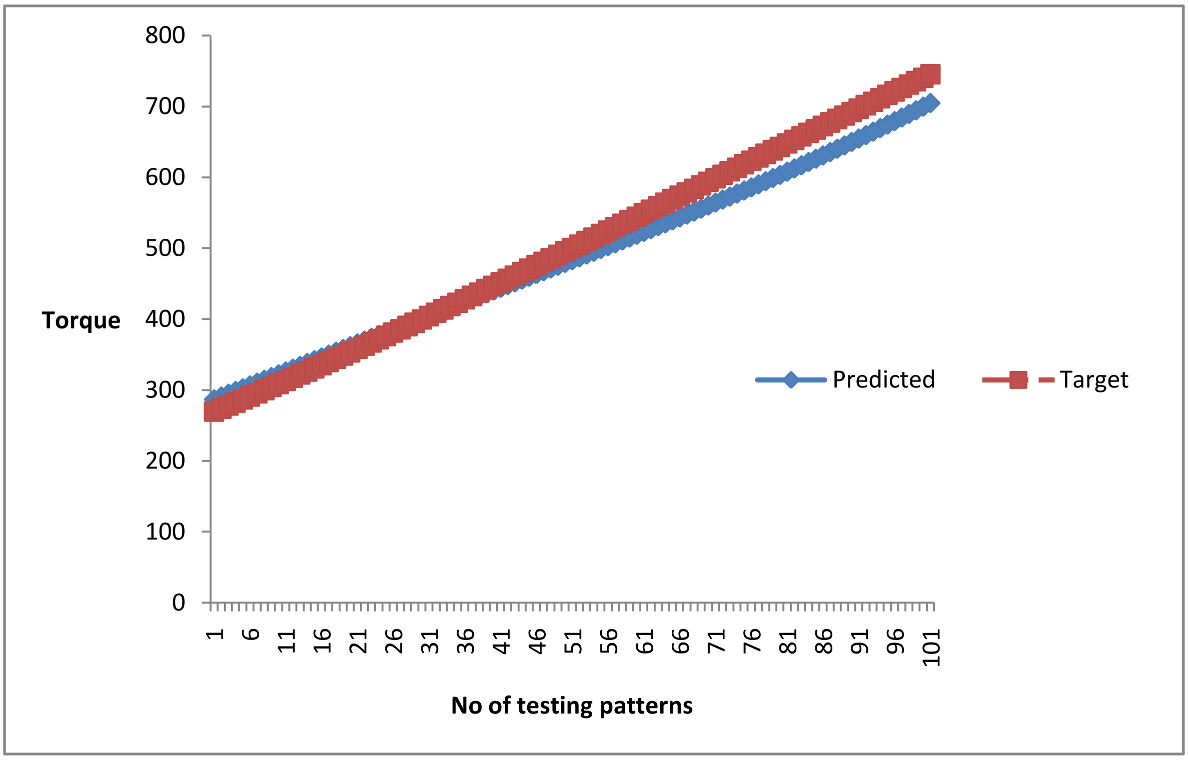

Fig 5: shows the predicated values of cascade feed forward neural network against the target values.

Fig. 6 shows that radial basis function neural network outperformed the other two types since in the case of radial basic function networks it is necessary to correctly initialise initial states; whereas in feed forward networks parameters are randomly initialised. Finally, the radial basic function clusters are separated by hyper spheres; whereas in neural networks, arbitrarily shaped hyper surfaces are used for separation. As seen from the architecture of the radial basic function network, the network behaves as a local approximation since the network's outputs are decided by hidden neurons in certain local receptive fields, whereas the feed forward network behaves globally. This is because the outputs are computed by all neurons [5].

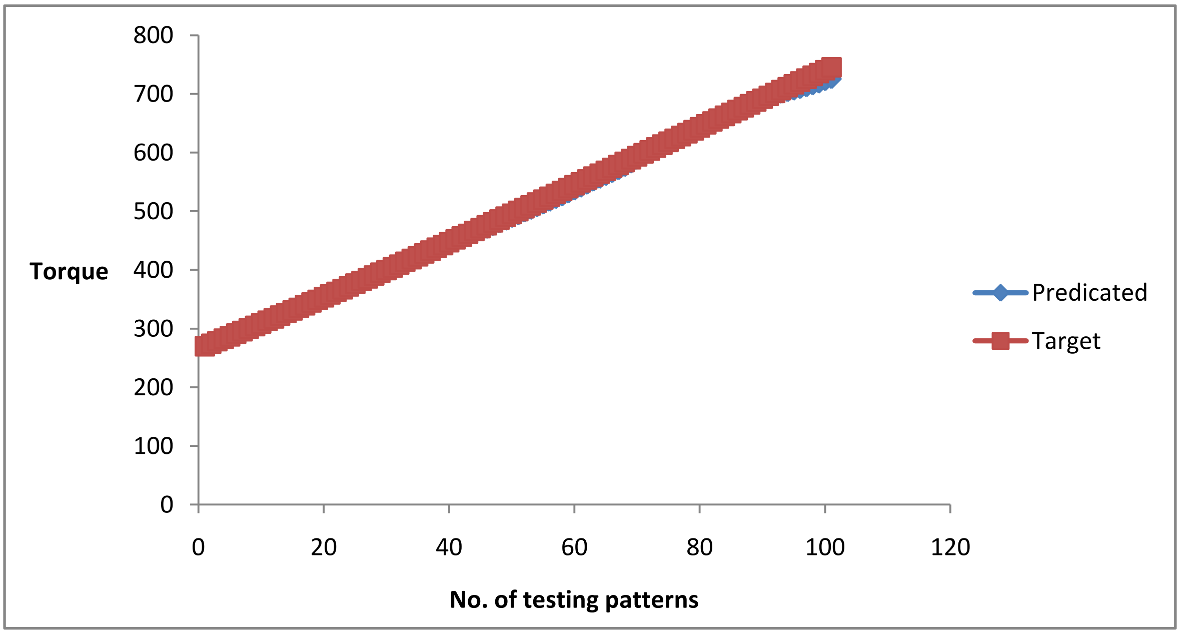

Fig. 6: shows the predicated values of radial basis function neural network against the target values.

As can be seen in Fig. 7, the performance of radial basis function network, the network displayed a clear distinction in performance among the networks.

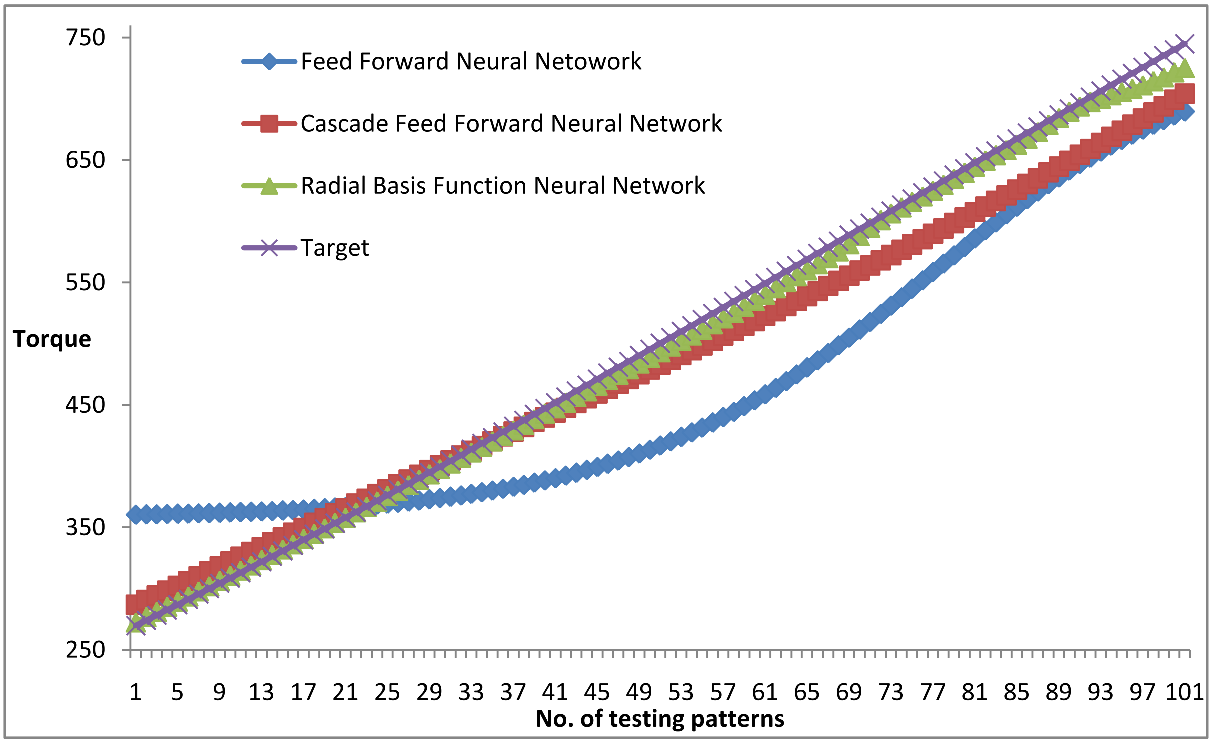

Fig7. : shows the predicated values of the three types of neural networks against the target values.

V. Conclusion and Discussion

This paper presents the application of predicting torque for direct current motor engines using neural network models. The paper aims at studying three different types of neural networks, these types are feed forward neural networks, cascade feed forward neural networks and radial basis functions. Three learning algorithm types are used to train these networks. These algorithms are namely: the back propagation algorithm, marquarder levenbregr backbropagation and orthogonal least square learning algorithm. The following main points concluded in this paper are as follows:

1) The feed forward neural network is very similar in architecture to cascade feed forward neural networks.
2) As mentioned above, radial basis function can have only three layers, whereas the feed forward can have more than three layers. In this spirit the radial basic function is much simpler than feed forward. This important feature makes the training process for the radial basis function network much faster than that of feed forward.
3) Another important point of difference between the radial basic function and feed forward is that in the case of radial basic function networks it is necessary to correctly initialise initial states; whereas in feed forward networks parameters are randomly initialised. Finally, the radial basic function clusters are separated by hyper spheres; whereas in neural networks, arbitrarily shaped hyper surfaces are used for separation.
4) As seen from the architecture of the radial basic function network, the network behaves as a local approximation since the network's outputs are decided by hidden neurons in certain local receptive fields, whereas the feed forward network behaves globally. This is because the outputs are computed by all neurons.
5) The results show that the radial basic function outperformed both feed forward and cascade feed forward networks.

References

[1] Adepoju G. A., Aborisade, D.O, Eluwole O. T. , Speed Forecast of DC Motor Using Artificial Neural Network, *International Journal of Applied Science and Technology, Vol. 1 No. 6; November* 2011.

[2] Phan Quoc Dzung, Le Minh Phuong , ANN - Control System DC Motor, *Faculty of Electrical & Electronic Engineering. HCMC University of Technology. Ho Chi Minh City – Vietnam,* 2005.

[3] Amit Atri, Md. Ilyas, Speed Control of DC Motor using Neural Network Configuration, *International Journal of Advanced Research in Computer Science and Software Engineering Volume 2, Issue 5, ISSN: 2277 128X* , May 2012.

[4] T. Rashid and M-T. Kechadi, Study of Artificial Neural Networks for Daily Peak Electricity Load Forecasting, the 2nd Int’l. Conference on Information Technology (ICIT 2005) Amman, Jordan, 2005.

[5] Tiantian Xie, Hao Yu and Bogdan Wilamowski, Comparison between Traditional Neural Networks and Radial Basis Function Networks, *Electrical and Computer Engineering, Auburn University, pp- 1194-1199 978-1-4244-9312-IEEE,* 2011.

[6] J. Moody and C. J. Darken, "Fast Learning in Networks of Locally Tuned Processing Units*," Neural Computation, vol. 1, no. 2, pp. 281294,* 1989.

[7] B. M. Wilamowski and H. Yu, Improved Computation for Levenberg Marquardt Training, *IEEE Trans. on Neural Networks, vol. 21, no. 6, pp. 930-937, June* 2010.

[8] B. M. Wilamowski and H. Yu, *Neural Network Learning Without Backpropagation, IEEE Trans. on Neural Networks, vol. 21, no.11, pp. 1793-1803, Nov*ember 2010.

[9] Vitaly Schetinin, A Learning Algorithm for Evolving Cascade Neural Networks Neural Processing Letter, *TheorieLabor, Friedrich-Schiller University of Jena,* . Kluwer,*17:21-31*, 2003.

[10] Sumit Goyal and Gyandera Kumar Goyal, Cascade and Feedforward Backpropagation Artificial Neural Network Models For Prediction of Sensory Quality of Instant Coffee Flavoured Sterilized Drink, *Canadian Journal on Artificial Intelligence, Machine Learning and Pattern Recognition Vol. 2, No. 6, August* 2011.

[11] A. W. Jayawardena, d. A. K. Fernando & m. C. Zhou. Comparison of Multilayer Perceptron and Radial Basis Function networks as tools for flood Forecasting, *Department of Civil and Structural Engineering, The University of Hong Kong, Pokjulam Road, Kong Kong, Destructive Water: Water-Caused Natural Disasters, their Abatement and Control (Proceedings of the Conference held at Anaheim, California, June 1996). IAHS Publ. no. 239,* 1997.

[12] R.A. Finan, A.T. Sapeluk, and R.I. Dampe, *Comparison of Multilayer and Radial Basis Function Neural Networks for Text-Dependent Speaker Recognition*, 1996.

