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A Review on DC Motor Speed Control using Artificial Neural Network

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Abstract: **This paper presents an insight into the speed control of DC motor using artificial neural network controller to meet the desired speed. The neural network scheme consist of two parts: one is neural estimator, which is used to estimate the motor speed and the other is the neural controller, which is used to generate a control signal for a converter. These two neural networks are trained by feed forward neural network algorithm. Simulation results are presented to demonstrate the effectiveness and advantage of control system of DC motor with ANN in comparison with conventional control scheme. For the comparison we used PID control.**

Keyword: **DC motor, Artificial Neural Network (ANN), Feed Forward Neural Network Algorithm.**

I. INTRODUCTION

Conventional direct current electric machines and alternating current induction and synchronous electric machines have traditionally been the three cornerstones serving daily electric motors needs from small household appliances to large industrial plants. Recent technological advances in computing power and motor drive systems have allowed an even further increase in application demands on electric motors. Through the years, even AC power system clearly winning out over DC system, DC motors still continued to be significant fraction in machinery purchased each year [1]. There are two types of DC motors: brushed and brushless motor.

A brushless DC motor (BLDC) is a synchronous electric motor which is power driven by direct-current electricity (DC) and which has an electronically controlled commutation system, instead of a mechanical commutation system based on brushes. In such motors, current and torque, voltage and rpm are linearly related. In BLDC motor, There are two sub-types used which are the Stepper Motor type that may have more poles on the stator and the Reluctance Motor.

BLDC motors are considered to be more efficient than brushed DC motors. This means that for the same input power, a BLDC motor will convert more electrical power into mechanical power than a brushed motor, mostly due to the absence of friction of brushes. The enhanced efficiency is greatest in the no-load and low-load region of the motor's performance curve. Under high mechanical loads, BLDC motors and high quality brushed motors are comparable in efficiency. Brushless DC motors are commonly used where precise speed control is necessary,

Nowadays, the field of electrical power system control in general and motor control in particular has been researching broadly. The new technologies are applied to these in order to design the complicated technology system. One of these new technologies is Artificial Neural Network (ANNs) which based on the operating principle of human being nerve neural. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons [2].

The objective of the Artificial Neural Network Controller Design for DC motor using MATLAB an application is it must control the speed of DC motor with Artificial Neural Network controller using MATLAB application which the design of the ANN controller is provided and can be tune [3] [4].

II. DC MOTOR BASIC PRINCIPLE

1. Energy Conversion

If electrical energy is supplied to a conductor lying perpendicular to a magnetic field, the interaction of current flowing in the conductor and the magnetic

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field will produce mechanical force (and therefore, mechanical energy).

2. Value of Mechanical Force

There are two conditions which are necessary to produce a force on the conductor. The conductor must be carrying current, and must be within a magnetic field. When these two conditions exist, a force will be applied to the conductor, which will attempt to move the conductor in a direction perpendicular to the magnetic field [27]. This is the basic theory by which all DC motors operate. The force exerted upon the conductor can be expressed as follows.

$$F = B\,i\,l \text{ Newton} \qquad (1)$$

Where B is the density of the magnetic field, l is the length of conductor, and i the value of current flowing in the conductor. The direction of motion can be found using Fleming's Left Hand Rule.

3. Principle of operation

Consider a coil in a magnetic field of flux density B (figure 4). When the two ends of the coil are connected across a DC voltage source, current I flows through it. A force is exerted on the coil as a result of the interaction of magnetic field and electric current. The force on the two sides of the coil is such that the coil starts to move in the direction of force.

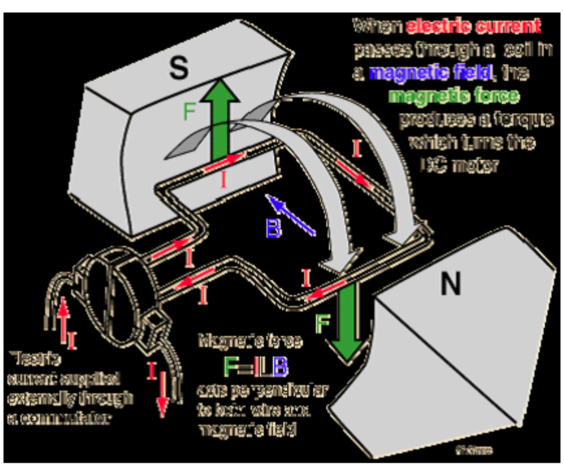

Figure 1: DC Motor

In an actual DC motor, several such coils are wound on the rotor, all of which experience force, resulting in rotation. The greater the current in the wire, or the greater the magnetic field, the faster the wire moves because of the greater force created. At the same time this torque is being produced, the conductors are moving in a magnetic field. At different positions, the flux linked with it changes, which causes an emf to be induced (e = d/dt) as shown in figure 5. This voltage is in opposition to the voltage that causes current flow through the conductor and is referred to as a counter-voltage or back emf.

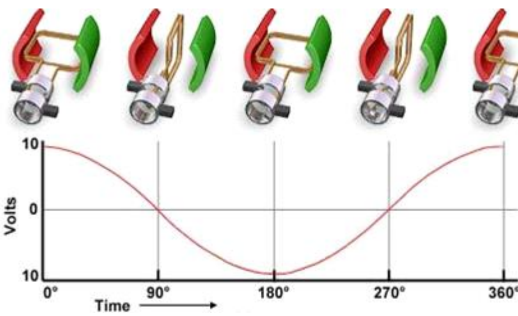

Figure 2: waveform

The value of current flowing through the armature is dependent upon the difference between the applied voltage and this counter-voltage. The current due to this counter-voltage tends to oppose the very cause for its production according to Lenz's law. It results in the rotor slowing down. Eventually, the rotor slows just enough so that the force created by the magnetic field (F = Bil) equals the load force applied on the shaft. Then the system moves at constant velocity.

4. Torque Developed

The equation for torque developed in a DC motor can be derived as follows.

The force on one coil of wire F =i l x B Newton (1)

Note that l and B are vector quantities

Since B =/A where A is the area of the coil,

Therefore the torque for a multi turn coil with an armature current of Ia:

T = KIa (2)

Where f is the flux/pole in weber, K is a constant depending on coil geometry, and Ia is the current flowing in the armature winding.

Note: Torque T is a function of force and the distance, equation (2) lumps all the constant parameters (eg. length, area and distance) in constant K.

The mechanical power generated is the product of the machine torque and the mechanical speed of rotation,

Or, Pm = T

Pm = K Ia (3)

5. Induced Counter-voltage (Back emf):

Due to the rotation of this coil in the magnetic field, the flux linked with it changes at different positions, which causes an emf to be induced.

The induced emf in a single coil e=

Since the flux linking the coil,=

Induced voltage e=

The total emf induced in the motor by several such coils wound on the rotor can be obtained by integrating equation (4), and expressed as:

= K (5)

The electrical power generated by the machine is given by:

= Ia= K Ia (6)

6. DC Motor Equivalent circuit

The schematic diagram for a DC motor is shown below. A DC motor has two distinct circuits: Field circuit and armature circuit. The input is electrical power and the output is mechanical power. In this equivalent circuit, the field winding is supplied from a separate DC voltage source of voltage Vf. Rf and Lf represent the resistance and inductance of the field winding. The current if produced in the winding establishes the magnetic field necessary for motor operation. In the armature (rotor) circuit, VT is the voltage applied across the motor terminals, Ia is the current flowing in the armature circuit, Ra is the resistance of the armature winding, and Eb is the total voltage induced in the armature [21] [22].

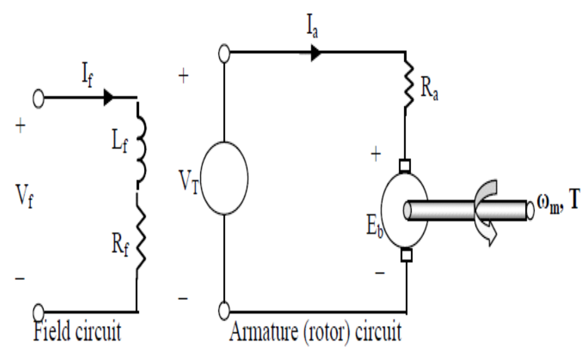

Figure 3: equivalent ckt diagram

7. Voltage Equation

Applying KVL in the armature circuit of Figure

VT = Eb + IaRa (7)

where VT is voltage applied to the armature terminals of the motor and Ra is the resistance of the armature winding.

Applying KVL in the field circuit of Figure

Vf = Rf If

III. ANN CONTROL

ANN controller architecture employed here is Non linear Auto Regressive Model reference Adaptive Controller [13]. Computations required for this controller is quite less. It is simply a rearrangement of the neural network plant model, which is trained offline, in batch form. It consists of reference, plant output and control signal. The plant output is forced to track the reference model output. Here, the effect of controller changes on plant output is predicted. It permits the updating of controller parameters. In the study, the frequency deviations, tie-line power deviation and load perturbation of the area are chosen as the neural network controller inputs [5]. Control signals applied to the governors in the area act as the outputs of the neural network. The data required for the ANN controller training is obtained by designing the Reference Model Neural Network and applying to the power system with step response load disturbance [7].

NARMA-L2 is one of the neural network architecture that has been implemented in the MATLAB for prediction and control. NARMA-L2 controller design is performed by two stages. 1. System identification and 2. Control design. In the system identification stage, the neural network model of the plant which is to be controlled is designed. For controller design, the plant model which is identified is used. The neurocontroller designed is referred by two different names. (i) NARMA-L2 control and (ii) Feedback Linearization control. When the plant model is in companion form, then it is said to be NARMA-L2 control and when the plant model can be approximated by companion form is feedback linearization control [11]. In NARMA-L2 control, the controller design is simply the rearrangement of plant model, which is trained offline, in batch form. It requires the least computation than model predictive and model reference controllers. If neural network is used as a controller, the parameters of NARMA-L2 have to be adjusted to achieve on line control. Only approximated methods are used in practice for controlling [12].

IV. Feed forward neural network structure

Recently, computational intelligence systems and among them neural networks, which in fact are model free dynamics, have been used widely for approximation functions and mappings. The main feature of neural networks is their ability to learn from samples and generalizing them and also their ability to adapt themselves to the changes in the environment. In fact, neural networks are very suitable for problems in the real world. These net-works with participation of a special kind of parallel processing are able to provide the modeling of any kind of nonlinear relations. Higher accuracy, robustness, generalized capability, parallel processing, learning static and dynamic model of MIMO systems on collected data and its simple implementation are some of the importance characteristics of the neural network that caused wide applications of this technique in different branches of sciences and industries, especially in designing of the non-linear control systems [9] [20]. The salient feature of artificial intelligent technique is that they provide a model-free description of control systems and do not require the ac-curate model of the plant. Thus, they are very suitable

There are some deviations and uncertainties due to changes in system parameters, characteristics and load variations in power systems that for the controller design have to be considered. On the other hand, very high (and unknown) model order, uncertain connection between subsystems; broad parameter variations and elaborate organizational structure of the power system preclude direct application of standard robust control methodologies. In order to overcome this drawback, we propose a new Non-linear Artificial Neural Network (NANN) controller based on μ-synthesis technique. Figure 5 shows the designing procedure of the NANN proposed controller for two-area power system. The Multi Layer Perception (MLP) neural networks for the design of the nonlinear AGC controller in two areas power systems are being used.

Since the objective of controller design in an interconnected power system is damping of the frequency and tie-line power deviations and in such a way minimizing transient oscillation under different load conditions. Thus, frequency and tie-line power deviations are chosen as the neural network controller inputs. Moreover, in order to evaluate the control signal (u), the NANN controller is using a piece of information which is not used in the conventional and modern controller (an estimate of the load perturbation _ ˆ PDi). In general, the load perturbation of the large system is not directly measurable. Therefore, it must be estimated by a lin-ear estimator or by a nonlinear neural network estimator, if the nonlinearities in the system justify it. Such an estimator takes as inputs a series of k samples of the frequency fluctuations at the output of the generator [_F(n)_F(n − 1) · · ·_F(n − k + 1)]T and esti- mates the instantaneous value of the load perturbation based on this input vector. The implementation of such an estimator is beyond the scope of this paper. Here, we assume that the load estimate _ ˆ PDi is available, i.e _ ˆ PD(n) = _PD(n) .

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Neural Network Architecture and Training the NANN controller architecture employed here is a MLP neural network, which is shown in Fig. 6. The frequency deviations, tie-line power deviation and load perturbation of each area are chosen as the neural net-work controller inputs. The outputs of the neural network are the control signals, which are applied to the governors in each area. The data required for the NANN controller training is obtained from the designing and applying the μ–based robust controller to power system in different operating points with various load disturbances.

ANN controller used is a three-layer perception with one input, 15 neurons in the hidden layer, and one output. ANN Plant model is a three-layer perception with one input, 15 neurons in the hidden layer, and one output. The activation function of the networks neurons is trainlm function. 100 training samples have been taken to train 10 numbers of epochs. The proposed network has been trained by using the learning performance. Learning algorithms causes the adjustment of the weights so that the controlled system gives the desired results.

V. FUTURE SCOPE

While the research reported in this thesis shows that an ANN based adaptive controller performance is superior it still lacks with some limitations, which provides room for improvement. Such possible improvements are indicated below, as possible directions for further work.

In the present work the number of hidden layers and the number of neurons in the hidden layer are chosen by trial and error, bearing in mind that the smaller the number, the better it is in terms of both memory and time taken to implement the ANN. Further research can be done to find the optimum number of hidden layers and number of neurons in the hidden layer. Weights and biases updating feature of the ANN can compensate for both parameter changes and disturbances during operation. The uses of the adaptive learning rate in the proposed controller reduce the possibility of overshooting particularly during the transient conditions. The feedback provision in the modified ANN motor structure also enhances the stability of the system.

VI. CONCLUSION

The DC motor has been successfully controlled using an ANN. Two ANNs are trained to emulate functions: estimating the speed of DC motor and controlling the DC motor, Therefore, and so ANN can replace sensors speed in the model of the control systems. Using ANN, we don't have to calculate the parameters of the motor when designing the system control. It is shown an appreciable advantage of control system using ANNs, when parameters of the DC motor is variable during the operation of the motors. The satisfied ability of the system control with ANNs, ANN application can be used in adaptive controlling in the control system machine with complicated load. Nowadays, in order to implement the control systems using ANNs for DC motor on actual hardware, the ANN micro processor is being used.

Artificial Neural Network was used as a trainable non-linear mapping system. The speed of a self exited dc motor was controlled using the proposed ANN based adaptive controller. The details of development of the proposed controller were presented, including all analytical derivations. Programming and implementation details including hardware interfacing were given as well, for both the computer setup and the physical experimentation.

To controlled speed of DC Motor we used PID Controller for tuning the ANN to improve accuracy of speed. During the experimentation and after observing the results it has been proved that the proposed ANN based controller has a good ability to control the speed of the Separately excited dc motor, which shows the non-linearity behavior. Experimental results verify that this ANN and PID controllers both are controlled of speed of DC Motor with comparatively result.

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