SPEED CONTROL OF SEPARATELY EXCITED DC MOTOR USING ARTIFICIAL INTELLIGENT APPROACH

ALBINUS BERNARD

A project report submitted in partial
fulfillment of the requirement for the award of the

Master of Electrical Engineering

Faculty of Electrical and Electronic Engineering
Universiti Tun Hussein Onn Malaysia

JANUARY 2013

ABSTRACT

This paper presents the ability of Artificial Intelligent Neural Network *ANNs* for the separately excited dc motor drives. The mathematical model of the motor and neural network algorithm is derived. The controller consists two parts which is designed to estimate of motor speed and the other is which to generate a control signal for a converter. The separately excited dc motor has some advantages compare to the others type of motors and there are some special qualities that have in *ANNs* and because of that, *ANNs* can be trained to display the nonlinear relationship that the conventional tools could not implemented such as proportional-integral-differential (PID) controller. A neural network controller with learning technique based on back propagation algorithm is developed. These two neural are training by Levenberg-Marquardt. The effectiveness of the proposed method is verified by develop simulation model in MATLAB-Simulink program. The simulation results are presented to demonstrate the effectiveness and the proposed of this neural network controller produce significant improvement control performance and advantages of the control system DC motor with ANNs in comparison to the conventional controller without using ANNs.

ABSTRAK

Kertas kerja ini membentangkan tentang keupayaan *Artificial Intellengent* dalam penggunaan jaringan saraf tiruan *ANNs* bagi tujuan memacu motor AT teruja asing. Model untuk matematik bagi motor dan algoritma untuk jaringan saraf tiruan *ANNs* telah diterbitkan. Pengawal terdiri daripada dua bahagian yang direka bentuk untuk menganggarkan kelajuan motor dan yang sebahagian lagi menjana isyarat kawalan untuk penukar. Motor AT teruja asing mempunyai beberapa kelebihan berbanding dengan jenis motor yang lain serta terdapat beberapa sifat istimewa yang ada dalam *ANNs* dan kerana itu, *ANNs* boleh dilatih untuk memaparkan hubungan ciri-ciri tidak linear dengan alat konvensional yang mana tidak dapat dilaksanakan seperti pembezaan penting berkadar *(PID)* pengawal. Pengawal jaringan saraf dengan teknik pembelajaran dalam talian berdasarkan algoritma penyebaran belakang dibangunkan. Kedua-dua *neural* adalah dilatih dengan *Levenberg-Marquardt*. Keberkesanan kaedah yang disaran ini terbukti dengan membangunkan model simulasi dalam program *MATLAB-Simulink*. Keputusan simulasi dipaparkan bagi menunjukkan keberkesanan bahawa pengawal jaringan saraf pembelajaran yang dicadangkan itu menghasilkan peningkatan prestasi kawalan yang sejajar serta kelebihan yang ada pada sistem kawalan motor AT dengan menggunakan *ANNs* dibandingkan dengan pengawal konvensional tanpa menggunakan *ANNs*.

CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS AND ABBREVIATIONS

ANNs	-	Artificial Neural Networks
i_f	-	Field Current
U_f	-	Instantaneous Field Current
U_a	-	Instantaneous Armature Current
E_b	-	The Motor Back EMF
T_d	-	Torque Develop by Motor
$\omega_p(t)$	-	Rotor Speed (*rad/sec*)
$\mathrm{V_t(t)}$	-	Terminal Voltage (V)
$\mathrm{i_a(t)}$	-	Armature Current (A)
$\mathrm{T_L(t)}$	-	Load Torque (Nm)
J	-	Rotor Inertia ($\mathrm{Nm^2}$)
KF	-	Torque & Back EMF Constant ($\mathrm{NmA^{-1}}$)
B	-	Viscous Friction Coefficient (Nms)
$\mathrm{R_a}$	-	Armature and Field Resistance, (Ω)
$\mathrm{L_a}$	-	Armature and Field Inductance, (H)
T_m	-	Time Mechanical
MLP	-	Multilayer Perceptron
DC	-	Direct Current
SISO	-	Single Input Single Output
BP	-	Back Propagation
PID	-	Proportional Integral Derivative

CHAPTER 1

INTRODUCTION

1.1 Project Background

The development of high performance motor drives is very important in industrial applications. Generally, a high performance motor drive system must have good dynamic speed command tracking and load regulating response. The new technologies are emerging for control scheme. In recent two decades, soft computation is used widely. They are;

1) Artificial Neural Network (ANN)
2) Fuzzy Logic Set (FLS)
3) Fuzzy-Neural Network (FNN)
4) Genetic Algorithm Based System (GAB)
5) Genetic Algorithm Assisted System (GAA)

Neural network and fuzzy logic technique are quite different, and yet with unique capabilities useful in information processing by specifying mathematical relationships among numerous variables in complex system, performing mappings, control of nonlinear system to a degree not possible with conventional linear systems. Artificial Neural Networks (ANNs) is based on the operating principle of human nerve neural. This method is applied to control the motor speed [1]. For this project Neural Network technique, in speed control is used for a separately excited DC motor. The rotor speed of dc motor can be made to follow an arbitrary selected trajectory. The purpose is to achieve accurate trajectory control of the speed especially when the motor and load parameters are unknown.

1.2 Problem Statements

DC motor is still the most common choice if wide range of adjustable speed drive operation is specified. Among the three types of DC motors, such as series, shunt and separately excited DC motors. The separately excited DC motors are most often used. Different speed can be obtained by changing the armature voltage and the field voltage. The significant feature of separately excited DC motor configuration is its ability to produce high starting torque at low operation speed [2]. Although the conventional cascade PID technique [3] is widely used in DC motor speed and position control, it isn’t suitable for high performance cases, because of the low robustness of PID controller. Many researchers have been studying various new control techniques in order to improve the system performance [4-5].

This project proposed a new ability of artificial neural networks (ANNs) in estimating speed and controlling the separately excited dc motor to achieve the over speed self-regulating. The neural estimator used to estimate the motor speed and the neural controller is use to generate a control signal for a converter. From the simulation result are present to demonstrate the effectiveness of this neural and advantage of the control system DC motor with ANNs in comparison with the conventional scheme without ANNs. ANNs Controller is chosen to interface with the DC motor because in ANNs, Non-adaptive control systems have fixed parameters that are used to control a system. These types of controllers have proven to be very successful in controlling linear, or almost linear, systems.

1.3 Project Objectives

The major objective of this project is it must estimating and control the speed of DC motor with Artificial Neural Network controller using MATLAB application which the design of the ANNs controller is provided and can be tune. Each of the experimental result must be compared to the result of simulation, as a way to attain the closely approximation value that can be achieved in this system.

Its measurable objectives are as follows:

a) To identify the separately excited dc motor model for control speed condition.
b) To determine the performance based on the ANNs simulation.

1.4 Project Scopes

This project is primarily concerned with the control of the DC motor speed. The scopes of this project are:

a) To investigate ANNs controller which are used to estimating and control technique in simulation?
b) DC motor control model with ANNs and structure ANNs.
c) The performance analyses of the motor.

CHAPTER 2

LITERATURE REVIEW

2.1 DC Motor

The dc motors are used in various applications such as defence, industries, Robotics etc. The preferences are because of their simplicity, ease of application, reliability and favourable cost have long been a backbone of industrial applications. DC drives are less complex with a single power conversion from AC to DC. DC drives are normally less expensive for most horsepower ratings. DC motors have a long tradition used as adjustable speed machines and a wide range of options have evolved for this purpose. In these applications, the motor should be precisely controlled to give the desired performance. Many varieties of control schemes such as P, proportional integral (PI), proportional derivation integral (PID), adaptive, fuzzy logic controller (FLCs) and Artificial Neural Networks (ANNs) have been developed for speed control of dc motors.

2.1.1 Advantages of DC motor:

- Ease of control
- Deliver high starting torque
- Near-linear performance

2.1.2 Disadvantages of DC motor:

- High maintenance
- Large and expensive (compared to induction motor)
- Not suitable for high-speed operation due to commutator and brushes
- Not suitable in explosive or very clean environment

2.1.3 Classification of DC Motor:

- Separately exited DC motor
- Self-exited DC motor these are further classified into several types,
- DC shunt motor
- DC series motor
- Brushless DC motor
- Compound motors

2.2. Separately excited DC motor

Figure 2.1 shows the equivalent circuit of separately excited DC motor.

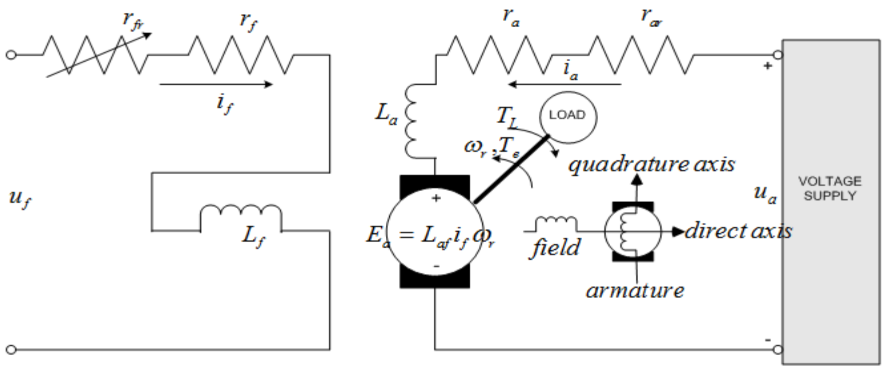

Figure 2.1: Equivalent circuit of separately excited DC motor

The field windings are used to excite the field flux. Armature current is supplied to the rotor via brush and commutator for the mechanical work. Interaction of field flux and armature current in the rotor produces torque.

2.2.1 Operation

i) When a separately excited motor is excited by a field current of i_f and an armature current of i_a flows in the circuit, the motor develops a back emf and a torque to balance the load torque at a particular speed.

ii) The i_f is independent of the i_a. Each windings are supplied separately. Any change in the armature current has no effect on the field current.

iii) The i_f is normally much less than the i_a.

2.2.2 Speed control techniques in separately excited dc motor:

i) Varying the armature voltage in the constant torque region.

ii) In the constant power region, field flux should be reduced to achieve speed above the rated speed.

2.2.3 Field And Armature Equations:

Instantaneous field current:

$$u_f = r_f i_f + L_f * di_f/dt \tag{2.1}$$

Where r_f and L_f are the field resistance and inductor, respectively.

Instantaneous armature current:

$$u_a = r_a i_a + L_a * di_a/dtE_a \tag{2.2}$$

Where r_a and L_a are the armature resistance and induction, respectively.

The motor back emf, which is also known as speed voltage, is expressed as:

$$E_b = K_v \omega i_f \tag{2.3}$$

K_v is the motor voltage constant (in V/A-rad/s) and □ is the motor speed (in rad/sec)

2.2.4 Basic Torque Equation:

For normal operation, the developed torque must be equal to the load torque plus the friction and inertia,i.e.:

$$T_d = J * \frac{d\omega}{dt} + B\omega + T_L \tag{2.4}$$

The torque developed by the motor is:

$$T_d = K_t i_f i_a \tag{2.5}$$

Where ($K_t = K_v$) is torque constant in V/A-rad/sec.

Sometimes it is written as:

$$T_d = K_t \Phi i_a \tag{2.6}$$

For normal operation, the developed torque must be equal to the load torque plus the friction and inertia, i.e.:

Where

B: viscous friction constant, (N.m/rad/s)

T_L: load torque (N.m)

J: inertia of the motor ($Kg.m^2$)

2.2.5 Steady state operation:

Under steady state operation, the time derivative is zero, assuming the motor is not saturated. Figure 2.2 shows a separately excited DC motor in steady state.

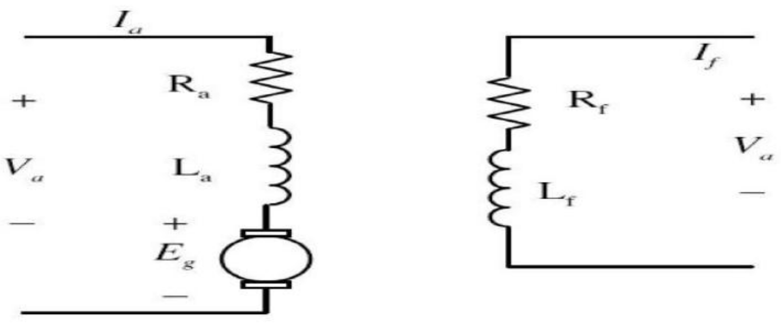

Figure 2.2: Separately excited DC motor in steady state

For the field circuit,

$$V_f = I_f R_f \tag{2.7}$$

The back emf is given by:

$$E_g = K_v \omega I_f \tag{2.8}$$

The armature circuit,

$$V_a = I_a R_a + E_g = I_a R_a + K_v \omega I_f \tag{2.9}$$

2.2.6 Steady state torque and speed:

The motor speed can be easily derived:

If R_a is a small value (which is usual), or when the motor is lightly loaded; i.e. I_a is small, that is if the field current is kept constant, the motor speed depends only on the supply voltage.

The developed torque is:

$$T_d = K_t I_f I_a = B\omega + T_L \tag{2.10}$$

The required power is:

$$P_d = T_d \omega \tag{2.11}$$

2.2.7 Torque and speed control:

From the derivation, several important facts can be deduced for steady state operation of DC motor. For a fixed field current, or flux (I_f), the torque demand can be satisfied by varying the armature current (I_a).

The motor speed can be varied by:

Controlling V_a (voltage control)

Controlling V_f (field control)

These observations lead to the application of variable DC voltage for controlling the speed and torque of DC motor.

2.2.8 Variable speed operation:

A family of steady state torque speed curves for a range of armature voltage can be drawn as figure 2.3.

The speed of DC motor can simply be set by applying the correct voltage.

Note that speed variation from no-load to full load (rated) can be quite small. It depends on the armature resistance.

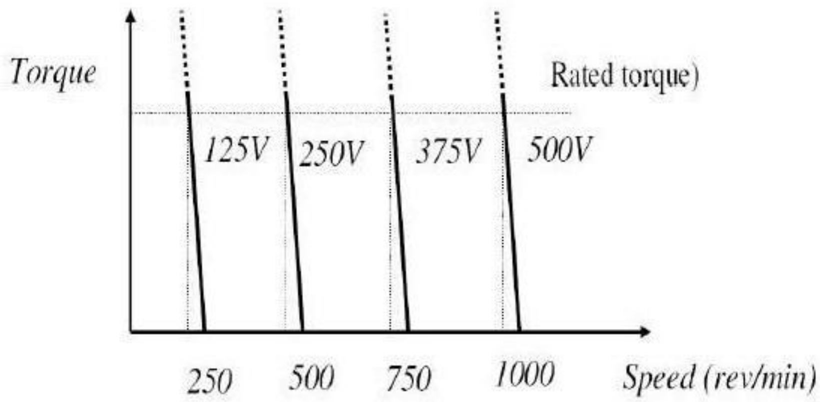

Figure 2.3: Torque vs speed characteristic for different armature voltages

2.2.9 Base speed and field weakening

Figure 2.4 show, torque vs speed and power vs speed characteristic of separately excited DC motor.

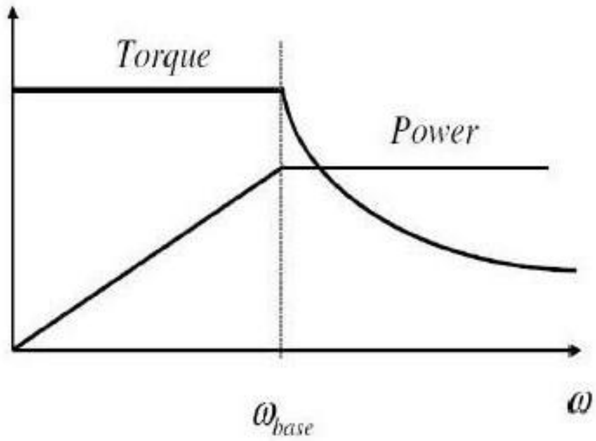

Figure 2.4: Torque vs speed and power vs speed characteristic of separately excited DC motor

Base speed (ω_{base}): the speed which corresponds to the rated V_a, rated I_a and rated I_f

Constant torque region ($\square > \omega_{base}$): I_a and I_f are maintained constant to met torque demand. V_a is varied to control the speed. Power increased with speed.

Constant power region ($\square > \omega_{base}$): V_a is maintained at the rated value and I_f is reduced to increase speed. However, the power developed by the motor (=torque * speed) remain constant. This phenomenon is known as field weakening.

2.3 Neural Network

Neural networks are wonderful tools, which permit the development of quantitative expressions without compromising the known complexity of the problem. This makes them ideal in circumstances where simplification of the problem, in order to make it mathematically tractable and would lead to an unacceptable loss of information. As pointed out by Ziman, there is a fine balance between over-idealizing the initial hypothesis in order to make it amenable to mathematical analysis, and abandoning reality [6].

2.3.1 What is a Neural Network

A neural network is a powerful data modelling tool that is able to capture and represent complex input/output relationships. The motivation for the development of neural network technology stemmed from the desire to develop an artificial system that could perform intelligent tasks similar to those performed by the human brain. Neural networks resemble the human brain in the following two ways:

i) A neural network acquires knowledge through learning.
ii) A neural network's knowledge is stored within inter-neuron connection strengths known as synaptic weights.

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, processing the information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurones) working in unison to solve specific problems. ANNs like people, learnt 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 neurones. This is true of ANNs as well.

The true power and advantage of neural networks lies in their ability to represent both linear and non-linear relationships and in their ability to learn these relationships directly from the data being modelled. Traditional linear models are simply inadequate when it comes to modelling data that contains non-linear characteristics.

2.3.2 Artificial Neural Networks

One type of network sees the nodes as ‘artificial neurons’. These are called artificial neural networks (ANNs). An artificial neuron is a computational model inspired in the natural neurons. Natural neurons receive signals through synapses located on the dendrites or membrane of the neuron. When the signals received are strong enough (surpass a certain threshold), the neuron is activated and emits a signal though the axon. This signal might be sent to another synapse, and might activate other neurons.

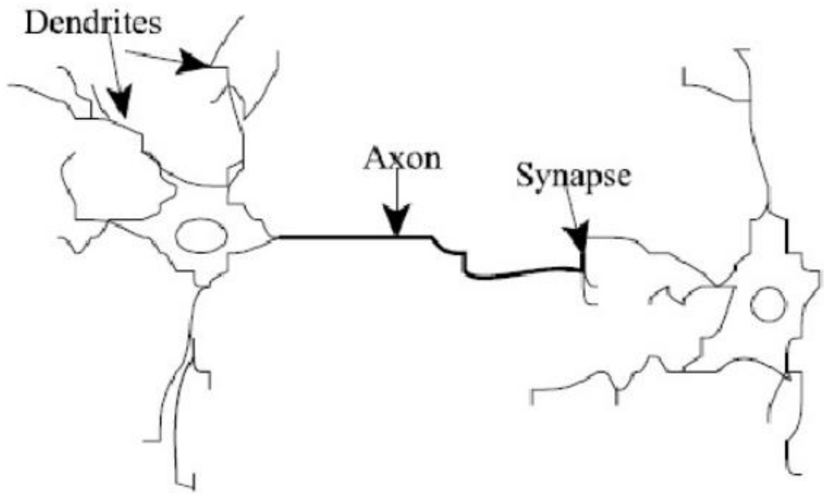

Figure 2.5: Natural neurons (artist's conception)

The complexity of real neurons is highly abstracted when modelling artificial neurons. These basically consist of inputs (like synapses), which are multiplied by weights (strength of the respective signals), and then computed by a mathematical function which determines the activation of the neuron. Another function (which may be the identity) computes the output of the artificial neuron(sometimes in dependence of a certain threshold). ANNs combine artificial neurons in order to process information.

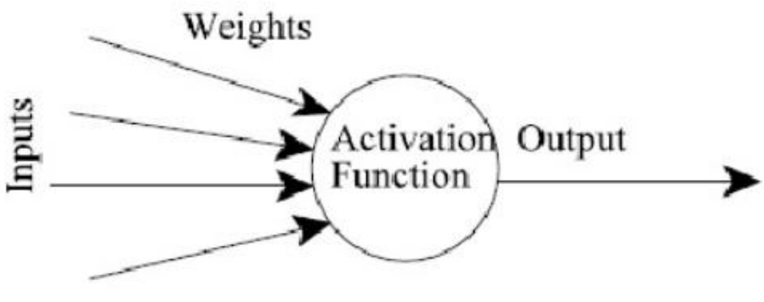

Figure 2.6: An Artificial Neuron

The higher a weight of an artificial neuron is, the stronger the input which is multiplied by it will be. Weights can also be negative, so we can say that the signal is inhibited by the negative weight. Depending on the weights, the computation of the neuron will be different. By adjusting the weights of an artificial neuron we can obtain the output we want for specific inputs. But when we have an ANN of hundreds or thousands of neurons, it would be quite complicated to find by hand all the necessary weights. But we can find algorithms which can adjust the weights of the ANN in order to obtain the desired output from the network. This process of adjusting the weights is called learning or training.

The number of types of ANNs and their uses is very high. Since the first neural model by McCulloch and Pitts (1943) there have been developed hundreds of different models considered as ANNs. The differences in them might be the functions, the accepted values, the topology, the learning algorithms, etc. Also there are many hybrid models where each neuron has more properties than the ones we are reviewing here.

Because of matters of space, we will present only an ANN which learns using the back propagation algorithm (Rumelhart and McClelland, 1986) for learning the appropriate weights, since it is one of the most common models used in ANNs, and many others are based on it. Since the function of ANNs is to process information, they are used mainly in fields related with it. There are a wide variety of ANNs that are used to model real neural networks, and study behaviour and control in animals and machines, but also there are ANNs which are used for engineering purposes, such as pattern recognition, forecasting, and data compression.

2.3.3 Neuron Model

A neuron with a single scalar input and no bias appears on the left below.

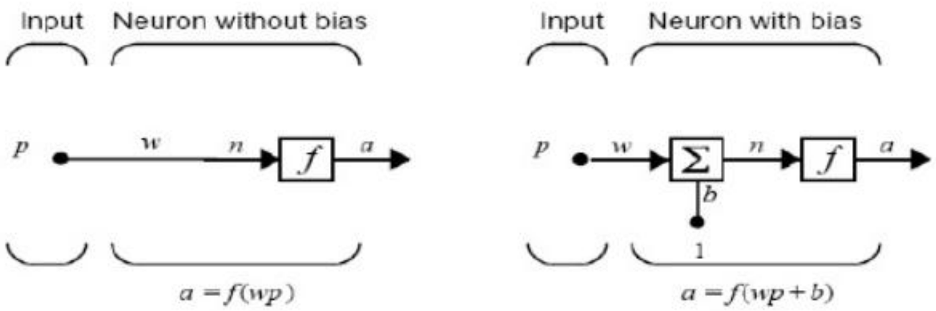

Figure 2.7: Neuron Model

The scalar input p is transmitted through a connection that multiplies its strength by the scalar weight w, to form the product wp, again a scalar. Here the weighted input wp is the only argument of the transfer function f, which produces the scalar output a. The neuron on the right has a scalar bias, b. You may view the bias as simply being added to the product wp as shown by the summing junction or as shifting the function f to the left by an amount b. The bias is much like a weight, except that it has a constant input of 1.

The transfer function net input n, again a scalar, is the sum of the weighted input wp and the bias b. This sum is the argument of the transfer function f. Here f is a transfer function, typically a step function or a sigmoid function, which takes the argument n and produces the output a.

2.3.3.1 Transfer Functions

Many transfer functions are included in this toolbox Matlab. Three of the most commonly used functions are shown on Figure 2.8, 2.9 and 2.10.

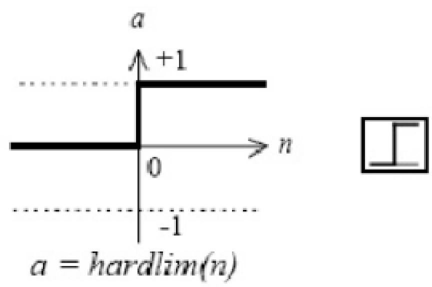

Figure 2.8: Hard-Limit Transfer Function

The hard-limit transfer function shown above limits the output of the neuron to either 0, if the net input argument n is less than 0; or 1, if n is greater than or equal to 0. We will use this function in Chapter 3 “Perceptrons” to create neurons that make classification decisions. The toolbox has a function, hardlim, to realize the mathematical hard-limit transfer function shown on Figure 2.8.

The linear transfer function is shown in Figure 2.9 below.

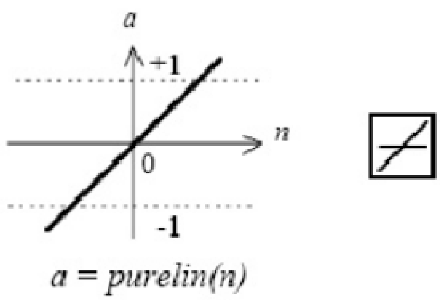

Figure 2.9: Linear Transfer Function

The sigmoid transfer function shown on Figure 2.10 takes the input, which may have any value between plus and minus infinity, and squashes the output into the range 0 to 1.

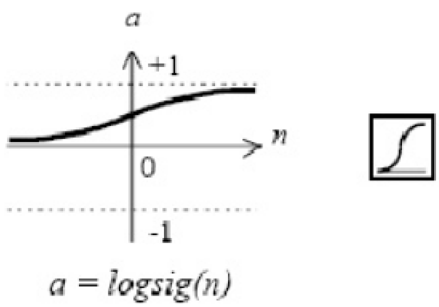

Figure 2.10: Log-Sigmoid Transfer Function

This transfer function is commonly used in back propagation networks, in part because it is differentiable. The symbol in the square to the right of each transfer function graph shown above represents the associated transfer function. These icons will replace the general f in the boxes of network diagrams to show the particular transfer function being used.

2.3.4 Historical Background

Neural network simulations appear to be a recent development. However, this field was established before the advent of computers, and has survived at least one major setback and several eras. Many important advances have been boosted by the use of inexpensive computer emulations. Following an initial period of enthusiasm, the field survived a period of frustration and disrepute. During this period when funding and professional support was minimal, important advances were made by relatively few researchers.

These pioneers were able to develop convincing technology which surpassed the limitations identified by Minsky and Papert. Minsky and Papert, published a book (in 1969) in which they summed up a general feeling of frustration (against neural networks) among researchers, and was thus accepted by most without further analysis [7]. Currently, the neural network field enjoys a resurgence of interest and a corresponding increase in funding.

2.3.5 Why use neural networks

Neural networks with their remarkable ability to derive meaning from complicated or imprecise data can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an expert in the category of information it has been given to analyse. This expert can then be used to provide projections given new situations of interest and answer what if questions. Other advantages include:

- Adaptive learning: An ability to learn how to do tasks based on the data given for training or initial experience.
- Self-Organisation: An ANN can create its own organisation or representation of the information it receives during learning time.
- Real Time Operation: ANN computations may be carried out in parallel, and special hardware devices are being designed and manufactured which take advantage of this capability.

Fault Tolerance via Redundant Information Coding: Partial destruction of a network leads to the corresponding degradation of performance. However, some network capabilities may be retained even with major network damage.

2.3.6 Neural Networks Versus Conventional Computer

Neural networks take a different approach to problem solving than that of conventional computers. Conventional computers used an algorithmic approach i.e. the computer follows a set of instructions in order to solve a problem. Unless the specific steps that the computer needs to follow are known the computer cannot solve the problem. That restricts the problem solving capability of conventional computers to problems that are already understood and know how to solve. But computers would be so much more useful if they could do things that human does not exactly know how to do.

Neural networks process information in a similar way the human brain does. The network is composed of a large number of highly interconnected processing elements (neurones) working in parallel to solve a specific problem. Neural networks learn by example. They cannot be programmed to perform a specific task. The examples must be selected carefully otherwise useful time is wasted or even worse the network might be functioning incorrectly. The disadvantage is that because the network finds out how to solve the problem by itself, its operation can be unpredictable.

On the other hand, conventional computers used a cognitive approach to problem solving; the way the problem is to solved must be known and stated in small unambiguous instructions. These instructions are then converted to a high level language program and then into machine code that the computer can understand. These machines are totally predictable; if anything goes wrong is due to a software or hardware fault.

Neural networks and conventional algorithmic computers are not in competition but complement each other. There are tasks that are more suited to an algorithmic approach like arithmetic operations and tasks that are more suited to neural networks. Even more, a large number of tasks, require systems that use a combination of the two approaches (normally a conventional computer is used to supervise the neural network) in order to perform at maximum efficiency.

2.3.7 Estimating The Speed Using Neural Networks

The rotor speed can be obtained by measuring the armature voltage, armature current and the derivative of the armature current. Because the armature voltage is varying between { d d } −U ,+U , the armature current also has fluctuation. Thus, before calculating the change of armature current it should be filtered (are not interested in the derivative of the fluctuation, only in the trend of the change of the armature current).

Experience showed that much better results can be achieved if the derivative of the armature voltage is also supplied to the neural network (in the same way as the armature current). The time-constant of the RiCi circuit for the derivative of armature voltage and current is calculated on the bases of equation. Thus, the neural network has four inputs:U,du/dt,i,di/dt while the output is the estimated rotor speed ω. Figure 2.11 show the structure of the neural network.

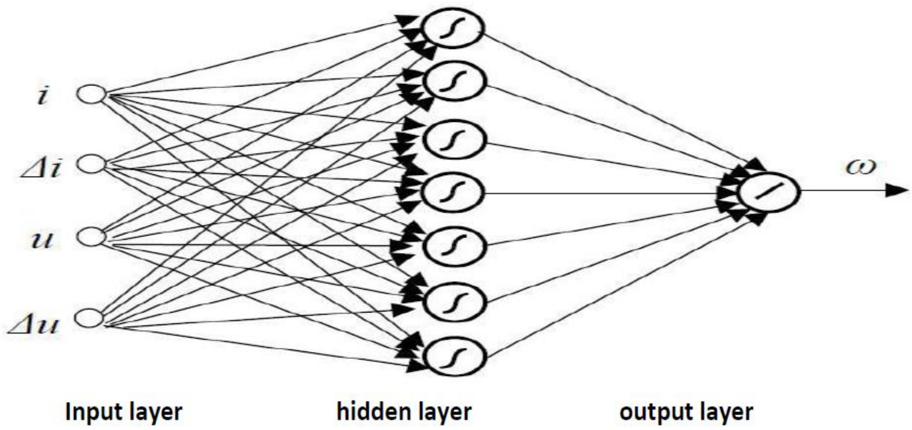

Figure 2.11: The structure of the neural network

The most common neural network model is the multilayer perceptron (MLP). This type of neural network is known as a supervised network because it requires a desired output in order to learn. The goal of this type of network is to create a model that correctly maps the input to the output using historical data so that the model can then be used to produce the output when the desired output is unknown. A graphical representation of a *MLP* is shown in Figure 2.12.

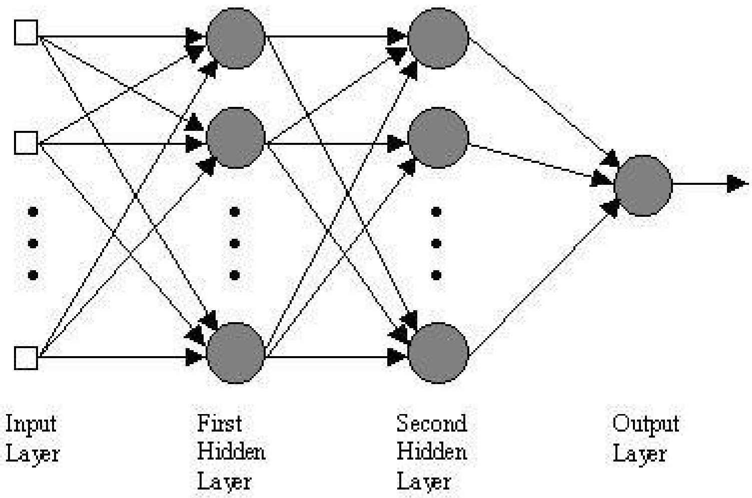

Figure 2.12: Block diagram of a two hidden layer multiplayer perceptron (MLP)

2.3.8 Description of Previous Methods

There are several technical or studies that was implemented by researchers related to dc motor speed control using ANNs. Table 2.1 show the previous method.

Table 2.1: Previous research in DC motor using different type of controller

No	Authors and year	Title of studies	Techniques used	Practical Application	Remarks
1.	Amit Atri, Md. Ilyas (2012)	Speed Control of DC Motor using Neural Network Configuration	Neural network	Experiment is done using Neural network control	Demonstrate the effectiveness of ANNs and advantage of the control system DC motor ANNs in comparison with the conventional scheme without ANNs.

2.	Jianguo Zhou, Youyi Wang and Rujing Zhou (2001)	Global Speed Control of Separately Excited DC Motor	Matlab / simulink	Using Matlab /Simulink to evaluate the proposed global speed controller for the field weakening operation of the separately Excited DC motor.	The global speed control problem for a separately excited DC motor is studied. The motor was firstly model in two local areas, the first one is a linear model when speed is under base speed, and the other is nonlinear one when the speed is above the bases peed.
3.	MA. Hoque M.R. Zaman and M.A Rahman, (1995)	Artificial Neural Network Based Permanent Magnet DC Motor Drives	Neural network	PM dc motor drive system with ANN speed controller is designed.	The ANNs based PM dc motor drive system is able to handle adequately the parameter variations and the changes in load.
4.	M.F. Chouikha and C.Aissi (1990)	Designand implementation of an intelligent controller using neural networks	Neural network	Investigating the idea of using neural networks for controlling complex systems.	Thus, the controller is able to use its past experience to improve its future performance. This approach has two main advantages: first it converges in cases where other methods have failed. Second, it is well suited for deductive as well as heuristic reasoning.

Table 2.1 (continued)

CHAPTER 3

METHODOLOGY

3.1 Introduction

The DC motor is the obvious proving ground for advanced control algorithms in electric drives due to the stable and straight forward characteristics associated with it. From a control system point of view, the DC motor can be considered as SISO plant, thereby eliminating the complications associated with a multi-input drive system. The proposed general block diagram for variable speed Separately excited DC motor using neural network controller is shown in Figure 3.1.

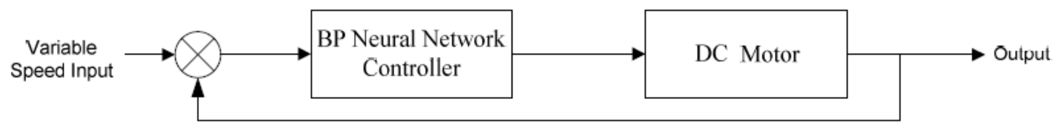

Figure 3.1: The block diagram of a variable speed neural network Separately Excited DC motor drive system

3.2 Mathematics modelling

To access the problem formulation the mathematical equation of separately excited dc motor needs to be understand. The separately excited dc motor model dynamics are described by a set of electrical and mechanical differential and algebraic equation in continuous time domain as follows;

$$KF_{\omega_p}(t) = -R_a \cdot i_a(t) - L_a \left[\frac{di_a(t)}{dt}\right] + V_t(t) \tag{3.1}$$

$$KF_{i_a}(t) = J[d\omega_p(t)/dt] + B\omega_p(t) + T_L(t) \tag{3.2}$$

Where,

$\omega_p(t)$	- rotor speed (*rad/sec*)
$V_t(t)$	- terminal voltage (V)
$i_a(t)$	- armature current (A)
$T_L(t)$	- load torque (Nm)
J	- rotor inertia (Nm^2)
KF	- torque & back emf constant (NmA^{-1})
B	- Viscous friction coefficient (Nms)
R_a	- Armature and field resistance, (Ω)
L_a	Armature and field inductance, (*H*)

From these equations mathematical model of the DC motor can be created. The model is presented in Figure 3.2.

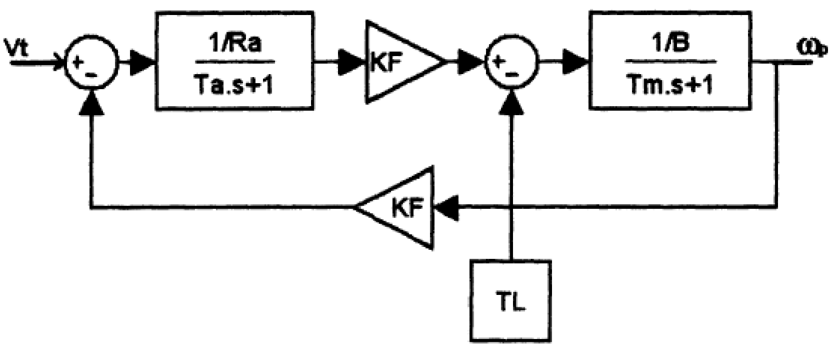

Figure 3.2: The mathematical model of a separately DC motor

3.2.1 The conventional control system of DC motor

There are many different methods to synthesize control systems of DC motor, but for this paper method used ANNs authors presented a conventional control system of DC motor as shown in Figure 3.3 page.

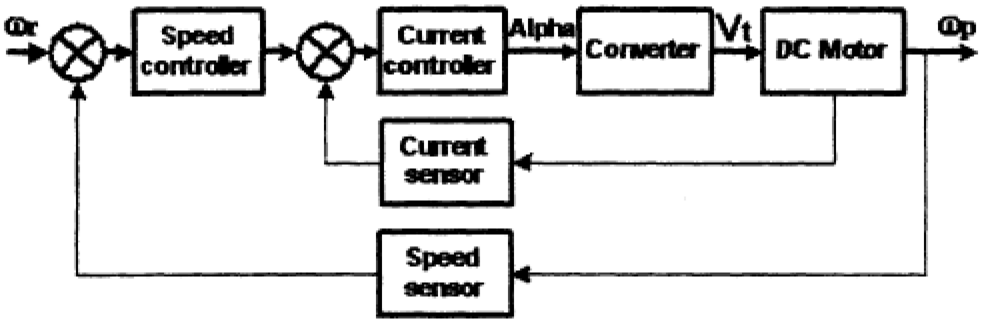

Figure 3.3: Conventional model of control system DC motor

3.2.2 The control system of DC motor using ANNs

The approach of neural network basically works on the provided priories information and makes a suitable decision for a given testing input based on the provided training in formation. This approach is analogous to the human controlling approach where all the past observations are taken as the reference information and are used as a decision variable. To obtain such estimation in current DC motor controlling approach the current DC motor drives are to be improved using such a learning approach.

In this paper a dual level neural network approach is designed for DC machine speed controlling. A dual level modelling provides a faster training and converging as compared to a single level neural modelling. For the realization of a dual level neural modelling, two-neuro architecture namely ANN-control and ANN-train is proposed. The 2 models of the control system of DC motor using ANNs is built with, ANN-train, and ANN-control unit where the network are trained to emulate a function: ANN-train to estimate the speed, ANN-control to control terminal voltage. The control system of DC motor using ANNs is presented in the Figure 3.4.

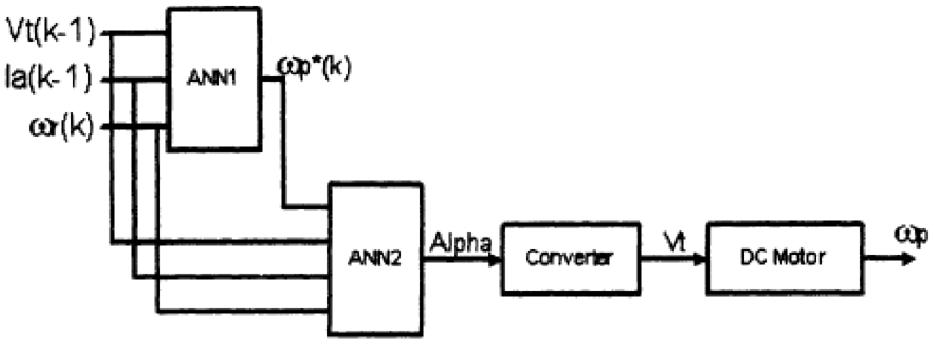

Figure 3.4: DC motor control model with ANNs

3.2.3 The structure and the process of learning ANNs

ANNs have been found to be effective systems for learning discriminates for patterns from a body of examples [8]. Activation signals of nodes in one layer are transmitted to the next layer through links which either attenuate or amplify the signal. ANNs are trained to emulate a function by presenting it with a representative set of input/output functional patterns. The back-propagation training technique adjusts the weights in all connecting links and thresholds in the nodes so that the difference between the actual output and target output are minimized for all given t raining patterns [9].

In designing and training the ANN is used emulate a function, the only fixed parameters are the number of inputs and outputs to the ANN, which are based on the input/output variables of the function. It is also widely accepted that maximum of two hidden layers are sufficient to learn any arbitrary nonlinearity [10]. However, the number of hidden neurons and the values of learning parameters, which are equally critical for satisfactory learning, are not supported by such well-established selection criteria. The choice is usually based on experience. The ultimate objective is to find a combination of parameters which gives a total error of required tolerance a reasonable number of t raining sweep [9,11,12].

The ANN1 structure is shown in Figure 3.5 and ANN2 in Figure 3.6. It consists of an input layer, output layer and one hidden layer. The input and hidden

REFERENCES

1. S.Weerasoorya and M.A Al-Sharkawi “Identification andcontrol of a DC Motor using back-propagation neuralnetworks” *IEEE transactions on Energy Conversion*, Vol.6,No.4 pp663-669, December 1991.
2. T.C. Burg, D. M. Dason, J. Hu, P. Vedagarbba, “Velocity tracking fora separately excited dc motor without velocity measurement”,Proceeding of the American Control Conference, pp.1051-1055,1994.
3. W. Leonhard, Control of Electrical Drives, .Td, Springer-Verlag, 1985.
4. Z. Liu and F. Luo, “Nonlinear multi-input multi-output control of dcmotor in fieldweakening region”, International Conference onElectric Machines and Drives, pp. 688-690, 1999.
5. M.R. Matausek, B.I. Jeftenic, D.M. Miljkovic, and M.Z. Bebic, “Gainscheduling control of dc motor drive with field weakening”, IEEETrans. on Industrial Electronics, pp. 153-162, Feb. 1996.
6. J. M. Ziman, Models of Disorder, Cambridge, Cambridge University Press, 1979.
7. Ben Krose and Patrick Van Der Smagt, An Introduction Neural Network, Nov 1996.
8. G.M. Scott, Knowledge- Based Artificial Neural Networks for ProcessModeling andControl, PhD. Thesis, University ofWisconsin, 1993.
9. S.Weerasoorya and M.A Al-Sharkawi "Identification and control of aDC Motor using back-propagation neural networks" IEEE transactions onEnergy Conversion, Vol.6, No.4 pp663-669, December 1991.
10. E. Levin, R. Gewirtzman, and G.F. Inbar, "Neural NetworkArchitecture for Adaptive System Modellinggand Control", Neural Networks,No 4(2) pp 185-191, 1991.

11. D. Psaltis A. Sideris and A.A. Yamamura, "A Multilayered Neural Network Controller", IEEE Control System Magazine, pp. 17-20, 1988.
12. B. Kosko, Neural Networks and Fuzzy Systems, Prentice-Hall International Inc, 1992.
13. Cajueiro, D. O., & Hemerly, E.M. (December, 2003). Direct Adaptive Control Using Feedforward Neural Networks.
14. IEEE Transaction, Volume-51, 1191-1214. DOURATSOS, I., & BARRY, J. (2007). NEURAL NETWORK BASED MODEL REFERENCE ADAPTIVE.
15. S.G German-Gankin – The computing modeling for power – electronic systems in Matlab, 2001.
16. Michael Negnevitsky – Artificial Intelligent A Guide to Intelligent systems.
17. Second Edition (2005). ADDISON Wesley Pearson Education Limited, 2002.