Scientific Journal Impact Factor (SJIF): 5.278
International Journal of Modern Trends in Engineering and Research
ISSN (ONLINE) : 2349 - 9745
ISSN (PRINT) : 2393 - 8161

ADAPTIVE CONTROL THEORY AND RECURRENT NEURAL NETWORK BASED BLDC CONTROL SYSTEM

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ABSTRACT: *Competitive advantages over AC motors make for DC motors to replace other electrical motors in applications stretching from high-speed automation to electric motorbikes. BLDC drives are very popular in many industries, at present automation are added standard, Virtual Z-source multilevel is a respectable optimal that can boost the output voltage of the drive. An novel soft computing based Recurrent Neural Network (RNN) based Virtual Z-source multilevel inverter, for BLDC motor drive control to make the system balanced when the load is unbalanced and to reduce the electrical torque pulsation. In this paper, the utilization of the RNN to tackle the selective harmonic elimination issue in INVERTER inverters is proposed. This strategy permits active voltage control of the crucial and besides concealment of a particular set of harmonics. The favorable principle position of the proposed technique is that it requires delicate processing switching angles. The scheme was actualized to assess its execution in the disposal of sounds in a inverter. The performance is evaluated in various emphasis levels of the different control models. From the outcomes, it has been demonstrated that the proposed method can achieve a reduced harmonics by relieving the predominant odd order harmonics. The results investigation has shown that the proposed RNN switching angles can keep away the higher order harmonics. Thus the created voltage waveform can keep up its harmonics free inverter. By utilizing the got Switching edges, the harmonics can be maintained a strategic distance. Thus the subjected inverter nourished BLDC can offer with not very many hazard components to the utilities. The proposed concept is analysed and implemented with MATLAB/SIMULINK software. The simulation results verify the correctnessof the theories and the effectiveness of the proposed approach.*

I. INTRODUCTION

BLDC motor is widely used motor drive for both domestic and industrial purpose due to exclusion of mechanical commutator and brushes. Rotor position can be evaluated by using sensor and sensor less technique. Hall sensor is used to estimate the rotor position in sensor technique whereas; in sensor less technique back emf is used to sense the rotor position.

In the Z-source inverter setup a one of a kind LC organize in the DC interface and a little Capacitor on the AC side of the diode front end is utilized. As Z-source inverter utilized for voltage lift and voltage buck by controlling the Shoot-through obligation cycle, sought AC yield voltage is created, considerably more noteworthy than the line voltage for voltage help operation or not as much as the line voltage for voltage buck operation. The novel Vitual Z-source MLI inverter framework offers ride-through ability amid voltage lists, enhances control figure, decrease music, enhances dependability, and broadens yield voltage run. The Z-source inverter has certain impediment when utilized as a part of customizable speed drive system.

The developments of BLDC drives, and various types of energy resources have given great opportunities for the implementation of medium- and high-power inverters. The main problemwith these applications is the frequency constraint of the pulse width modulation (PWM) which are limited by switching losses and electromagnetic interferences which is the results of high dV/dt. Thus, to overcome the mentioned problems, selective-harmonic-elimination- (SHE-) based optimal pulse width modulation (OPWM) are proposed which are able to reduce the switching frequency and the total harmonic distortion of output voltage. A typical multilevel inverter utilizes several DC voltage sources to provide a stepwise waveform in output voltage which makes a great development on output voltage THD while the output waveform approaches nearly sinusoidal waveform. Because of the complexity of the problem,in most studies on the SHE methods for multilevel inverters,it is assumed that only one switching angle per each voltagelevel is defined and the dc voltage sources are balanced (equalto each other).

But in practical applications, depending onthe output waveform and operation scheme of the inverter,the dc sources could be unbalanced or several switchings per each level are involved. SHE method is a modulationstrategy whose goal is to determine the proper switchingangles to eliminate the number of low-order harmonicswhich cause to minimize the output waveformTHD.TheSHE method requires low switching frequency and stepwisewaveform of output voltages to be applied.The maingoal in SHE method is to determine the switching angles inwhich with the obtained switching angles the fundamentalcomponent reaches to the desired value and the undesiredharmonics; basically low-order harmonics are eliminated. The defined objective function for SHEproblem includesa set of nonlinear transcendental equations which mayinvolve several local optima. Solving the SHE problem isavailablewith the help of several procedures. This work presents performance analysis of BLDC drive that is based on the Virtual Z-source (VZS) multilevel inverter with the novel optimum switching logic controller.

Volume 07, Issue 09, [September-2020] ISSN (Online):2349–9745 ; ISSN (Print):2393-8161

To overcome the classic voltage source and current Inverters limitations, Impedance (Z) Source Inverter is introduced for this work. On the way to different Inverter topologies, predominant features of Inverter (MLI) also attract the drives.

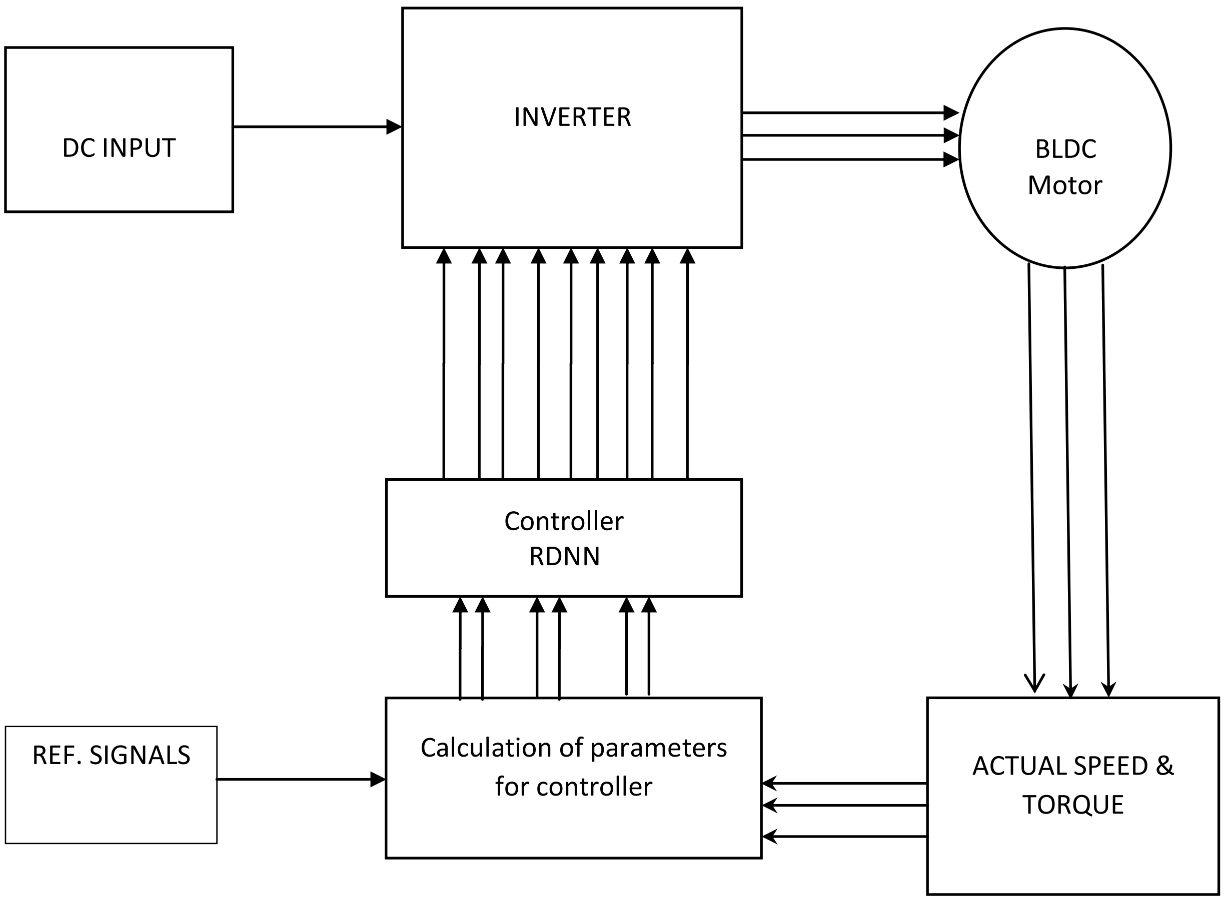


Figure 1.1 Closed Loop Operation of BLDC Motor Drive System with RNN Controller

By increasing the number of levels in the Inverter, the output voltages have more steps generating a staircase waveform which has a reduced harmonic distortion results in reduction of filter requirements. Great efforts are put towards reduction of Total Harmonic Distortion (THD) in MLI. It leads to proposing a Z Source Multilevel Inverter (ZSMLI) topology for the BLDC drive system. ZSMLI consists of active states and shoot through states. By properly adjusting the shoot through the time period of pulses in ZSMLI, the DC voltage can be bucked or boosted. Moreover the proper selection of firing pulses can limit the THD in the output voltage.

Volume 07, Issue 09, [September-2020] ISSN (Online):2349–9745 ; ISSN (Print):2393-8161

1.1RNN Controller Strategy

While interfacing the Voltage Source Inverter to the BLDC, an ideal controller is required to control the speed of BLDC motor in a closed loop.

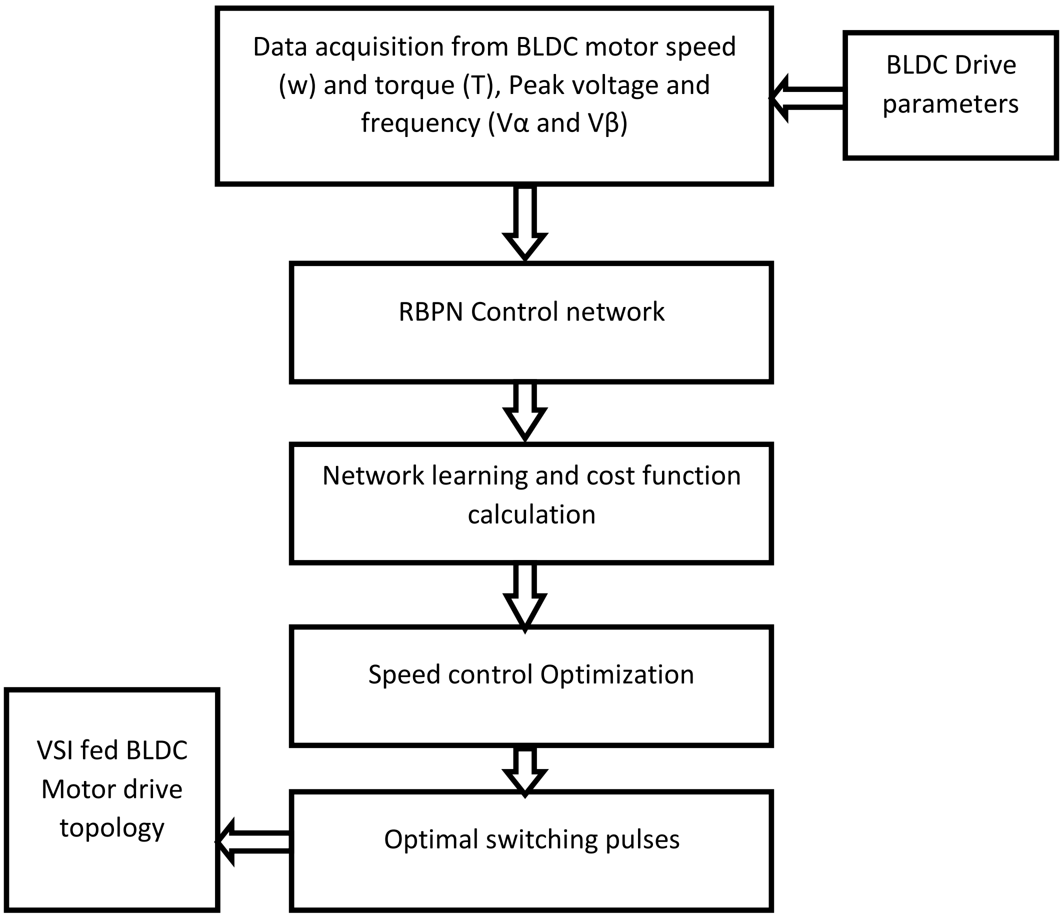


Figure 1.2 Proposed RNN Controller model flow

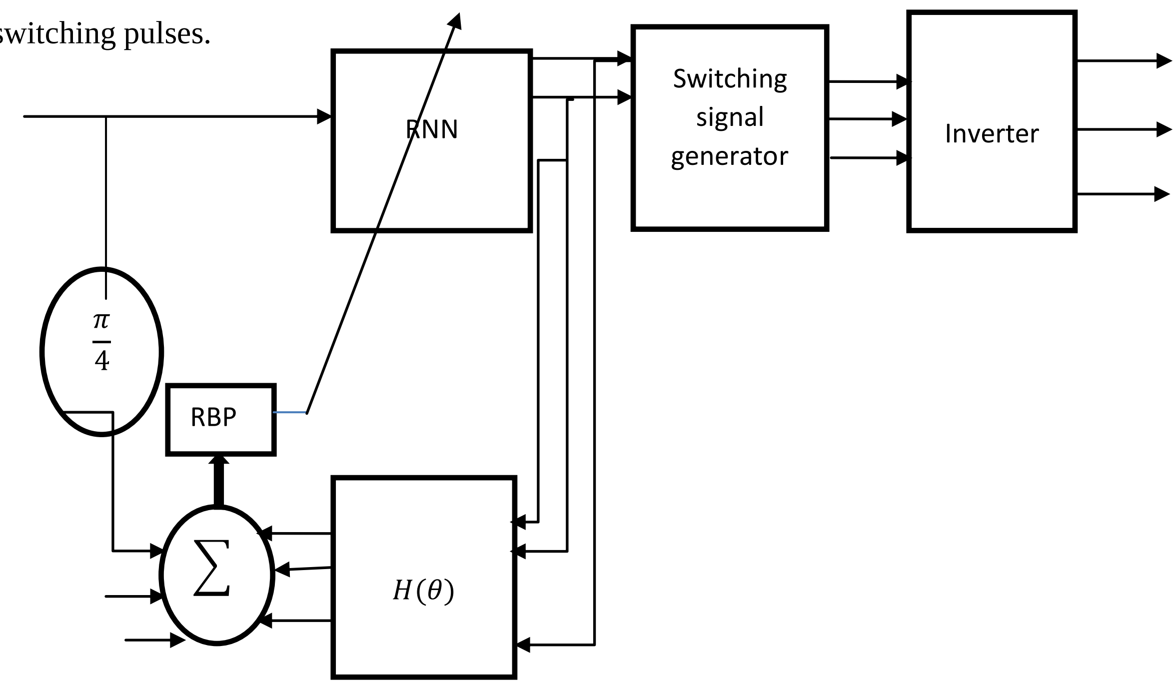
There are distinctive controllers used to monitor the performance metrics of the motor in the closed loop. The proposed controllers have expanded voltage gain, and system stability is more. So RNN controller is utilized to control the DC-interface voltage of voltage source inverter. This method is employed to measure the rotor position and depending upon the status detected switches in voltage source inverter are activated. Thus, the several switching angles arrived at the Inverter stages will bring about a greater extent of low order harmonics. The proposed methodology concentrates on the determination of switching schemes for the voltage

Volume 07, Issue 09, [September-2020] ISSN (Online):2349–9745 ; ISSN (Print):2393-8161

source inverter fed BLDC to remove the lower order harmonics using RNN. At first, RNN instrument is used to obtain different flux linkage data sets for the unique arrangement of the peak voltage, and frequency creates the voltages Vα and Vβ. These voltages are the contributions to the RNN to generate the switching pulses for the voltage source inverter.

The obtained data sets are used for developing the proposed neural network. The proposed RNN structure is then achieved to make the relating switching angles to the voltage source inverter switches based on the BLDC peak voltages. The proposed RNN controller is used to generate the switching angles which are then given to the voltage source inverter. The data set required for the RNN control is obtained by knowing the harmonic distortions by considering the different BLDC Parameters.

Artificial Neural Network Controller model is used to avoid switching complexity problem in the conventional Pulse width modulation techniques. So that the proposed control strategy employs the Resilient Back Propagation (RBP) algorithm with the equivalent nonlinear system conditions. Subsequently, the nonlinear system harmonics are eliminated by reducing the error using the necessary switching angles to the virtual Z Source Multilevel Inverter. In this condition, the neural system is set to create the switching angles in an approach to eliminate the first order Harmonics without the learning of the desired switching angles given by the Resilient Back Propagation algorithm. The optimized switching angles obtained from the Resilient Back Propagation (RBP) learning algorithm is the estimated outcome of the RNN, i.e., optimal switching pulses.



International Journal of Modern Trends in Engineering and Research (IJMTER)
Volume 07, Issue 09, [September-2020] **ISSN (Online):2349–9745 ; ISSN (Print):2393-8161**

Figure 1.3 RNN model for Optimal Harmonic Elimination

Figure 1.3 demonstrates the Resilient Back Propagation based RNN methodology of artificial neural network systems used for reduction of harmonics distortion. At this point, when the desired precision has been acquired, the yield of the RNN is used to create the control sequence of the Inverter. The RNN is trained by the RBP algorithm of the error between the desired solutions of the nonlinear system equations to eliminate the first harmonics and the output of this comparison using the switching angle given by the RNN.

1.2 Recurrent Neural Network Training Procedure

The network to be used for the proposed scheme comprises one input layer, one hidden layer, and an output layer. Switching pulses are given as learning sources, and their consonant voltages are taken as outputs. Recurrent Neural Networkis utilized to anticipate the Switching pulses and to control the voltage source inverter. The benefit of an RNN approach is its capacity to auto-tune the application without the necessity of specific function for the control. The RNN based neural system is very much developed by methods for the controlled features. The imaginative RBP network design comprises three input units, ‘n’ hidden units and one yield unit appears in figure.1.4

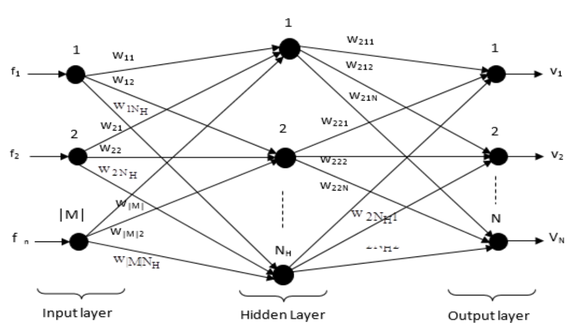


Figure 1.4 Training Structure of Recurrent Neural Network

Input layer: The Input layer takes input from the input document that contains data set for the preparation of the net. The example data set is arbitrarily chosen from the data set. The examples are utilized for training while others are utilized for testing the net. The line of the data set is known as an example speaking to a case of the input data set. The neural system peruses and explains consecutively all the input columns, and for everyone, it produces an output design speaking to the result of the whole procedure. Few neurons in this layer compared to the number of inputs to the neuronal system. This layer comprises a lot of nodes, i.e., which do not take part in the real flag change yet just transmits the flag to the accompanying layer. The center layer of nodes is known as the hidden layer since its qualities are not seen in the preparations.

Hidden Layers: Hidden layers in our created instrument are speaking to a decent non-direct component of the neural system. The sigmoid layers are utilized as hidden layers of the net. It can likewise be utilized to manufacture whatever layer of a neural system. These take inputs from the outputs of the input layer and apply for its presentation work. The output is sent to the outputting layer. This layer has an optional number of layers with a subjective number of neurons. The nodes in this layer participate in the flag alteration. Therefore, they are dynamic.

Output layer: The output segments enable a neural system to compose output designs in a record that are utilized for investigation of interruption. The quantity of neurons in the outputting layer is compared with the quantity of the output estimations of the neural system. The nodes in this layer are dynamic ones. The training procedure is described below.

Step1: Generate random weights in the interval w_{min}, w_{max} and share it to neurons of the hidden layer and the outer layer. Allocate unity weight to the neurons of the input layer.

Step 2: Give the training data set D as contribution to the system and decide the RBP error as takes after $e = V_r - V_{out}$ (1)

Where V_r and V_{out} are the objective function and the network outputs, respectively.

Step 3: From every output neuron of the network, the elements of $V_{out} = (V_h)$ can be determined as follows $V_h = \sum_{n=1}^{N_{Hid}} w_{nh} y_n$ (2)

Where, $y_n = \sum_{j=1}^{N_l} \frac{w_{jn}}{1+e^{-ikl}}$

Where N_{Hid} is the number of hidden neurons, w_{nh} is the assigned weight of the *n-h* link of the network and V_h is the output of the hth output neuron and y_n is the output of the n^{th} hidden neuron.

Step 4: By the attained RBP error, control the adjustment in weights as follows

$$\Delta w = \gamma . Vout. e \quad (3)$$

Where, the knowledge function γ, usually varies from 0.1 to 0.45.

Step 5: Regulate original weights as follows:

$$w = w + \Delta w \quad (4)$$

Step 6: Repeat the process from step (2), until RBP error gets reduced to the least value, mostly, the condition to be satisfied is $e<0.1$. Once the instruction process is performed, the network receives well prepared to evaluate any given unknown data.

The training process will be repeated many times to derive an averaged network as the Controlled final pulses. During the validation process, the VZMLI regions will be further identified using the Controlled pulses to switches in the topology.

1.3 Back Propagation Control in RNN

The back propagation through time, an augmentation of the well-known back provoking technique to dynamic models, has been considered as a restrictive calculation for preparing intermittent frameworks. The weight changes are relative to the measure of the inclination of an error function. E, leading to the following formula:

$$\Delta w_i(t) = -\mu \frac{\partial^+ E(t)}{\partial w_i} \quad (5)$$

Where, $\partial^+ E(t)/\partial w_i$ the ordered partial derivative of E concerning a weight is represented as the time index, and m is the learning rate. A suitable choice of the learning rate is vital to the advancement of the learning procedure and constitutes a critical imperative since the learning rate is basic to all weight refreshes. The Resilient Back Propagation endeavours to ease this inconvenience of back propagation through time by enabling each fitting parameter to have its progression measure, which is balanced among the learning procedure in light of the neighbourhood sight of the work, i.e., the indication of the individual incomplete subordinate at the current and the past generation. In that regard, the impact of the adjustment procedure is not covered by the impact of the measure of the parameter slope. Let $\partial^+ E(t)/\partial w_i$and $\partial^+ E(t-l)/\partial w_i$ denote the derivatives of E with respect to the present and the preceding epochs, respectively. Defining as n+ and n- the increase and attenuation factors, respectively, the step sizes are updated at each period according to the following conditions:

$$if \frac{\partial^{+}E(t)}{\partial w_i} \times \frac{\partial^{+}E(t-l)}{\partial w_i} > 0$$

$$then \Delta_i^{(t)} = min\left\{\mu^{+}.\Delta_i^{(t-1)}, \Delta_{max}\right\} \quad (6)$$

$$elseif \frac{\partial^{+}E(t)}{\partial w_i} \times \frac{\partial^{+}E(t-1)}{\partial w_i} < 0$$

$$then \Delta_i^{(t)} = max\left\{\mu^{-}.\Delta_i^{(t-1)}, \Delta_{max}\right\}$$

$$else \Delta_i^{(t)} = \Delta_i^{(t-1)}$$

$$\Delta w_{\boldsymbol{i}}(t) = -sign\left(\frac{\partial^{+}E(t)}{\partial w_i}\right).\Delta_i^{(t)} \quad (7)$$

Where,

$\partial^{+}E(t)/\partial w_i$ And $\partial^{+}E(t-l)/\partial w_i$ denote the particle derivatives

E=weight model

Compute gradient $=\frac{\partial^{+}E(t)}{\partial w_i}$

$\Delta_i^{(t)} = max\left\{\mu^{-}.\Delta_i^{(t-1)}, \Delta_{max}\right\}$ Maximum time for particle derivatives

$\Delta_i^{(t)} = min$ tMinimum time for particle derivatives

ANN is a powerful tool that is based on the behaviours of biological neurons and can represent nonlinear systems. The proposed Recurrent Neural Networkconsists of connected neurons that communicate by sending signals to each other along weighted connections.

Connection weights are changed by learning rule in the training process. The output y_j is expressed as follows

$$y_j = f\left(\sum w_{ji} x_i\right) \tag{8}$$

Where f is activation function, x_i is the input signal, and w_{ji} is connection weight. The sum of squared differences between the desired and actual values of the output neurons E is given by

$$E = \frac{1}{2}\sum_j \left(y_{dj} - y_j\right)^2 \tag{9}$$

Where y_{dj} is the aspired value of output neuron j, and y_j is the exact output of that neuron.

Recurrent Neural Networks (RNN) based solution for determining angles and generating PWM signals have been developed. For this purpose, the optimum 11-switching angles are determined by optimizing the objective function in Eq. (4.22) that are fit for switching angles of several modulation indexes and switching angles.

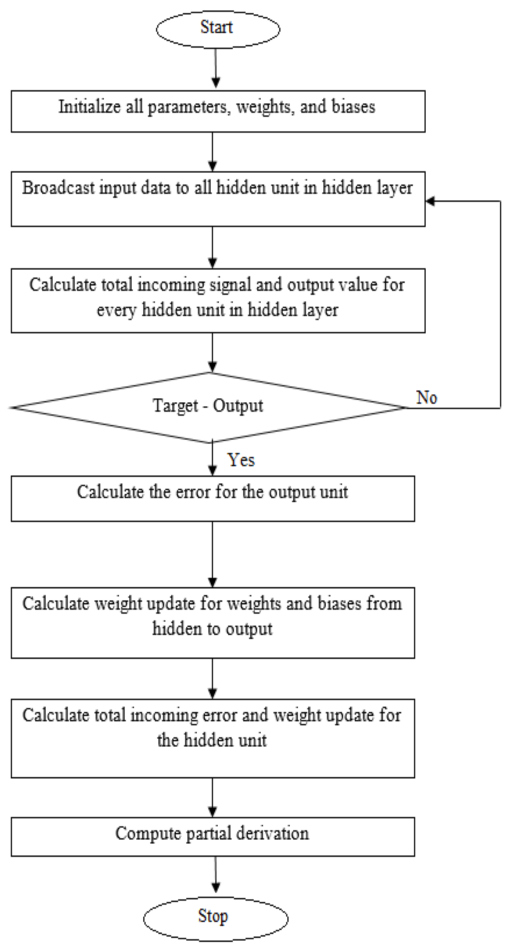


Figure 1.5 Flow Chart of Recurrent Neural Network

The operation and parameters of the Recurrent Neural Network algorithm are shown in figure 1.5. Resilient Propagation and Back Propagation are very much similar except for the weight update routine. Resilient propagation does not take into account the value of the partial derivative (error gradient) but rather considers only the sign of the error gradient to indicate the direction of the weight update. The Root Mean Square Error (RMSE), Coefficient of determination (R^2) and Mean Absolute Error (MAE) have been used to evaluate the performance of the RNN. These criteria are given by:

$$RMSE = \sqrt{\frac{\sum_{i-1}^{n}\left(y_{pre,i}-y_i\right)^2}{n}} \tag{10}$$

$$R^2 = 1 - \frac{\sum_{i-1}^{n}\left(y_{pre,i}-y_i\right)^2}{\sum_{i-1}^{n}\left(y_{mea,i}\right)^2} \tag{11}$$

$$MAE = \frac{\sum_{i-1}^{n}\left(y_{pre,i}-y_i\right)}{n} \tag{12}$$

Where n is the number of the data sample, y_{pre}, i is the predicted value, y_{mea}, i is the measured value and y_i is the value of a data sample. Acceptability of the RNN structure is proportional to a smaller RMSE and MAE values and with an amount of R^2 closer to 1.

II. RESULTS AND DISCUSSION

The implementation of the Recurrent Neural Network Control technique is performed on the working platform of Cloud server.

Table 2.1 Simulation Parameters of RNN

SYSTEM PARAMETER	SPECIFICATIONS
Input layer Neurons	3
Hidden layer Neurons	10
Output layer Neurons	7(switching angles)
Network Training Algorithm	Resilient Back Propagation(RBP)
Learning Rate	0.95

The proposed RNN system is executed in such a way that it can eliminate the total harmonic distortion. The RNN Simulation Parameter Specifications are shown in Table 2.1.

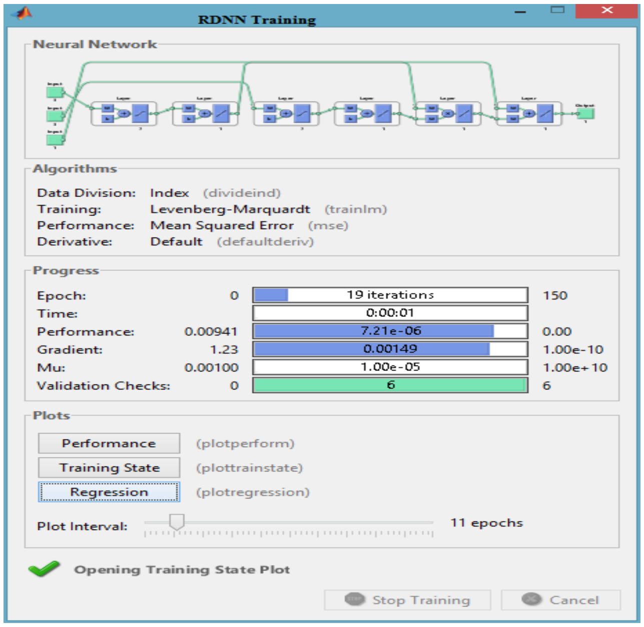


Figure 2.2 Training Structure of RNN

The figure 2.2 shows the training structure of proposed RNN based PMBLDC motor speed control system. The output voltage performance of the inverter obtained for the computed optimal switching angles and Inverter output voltage is provided in Figure 4.1

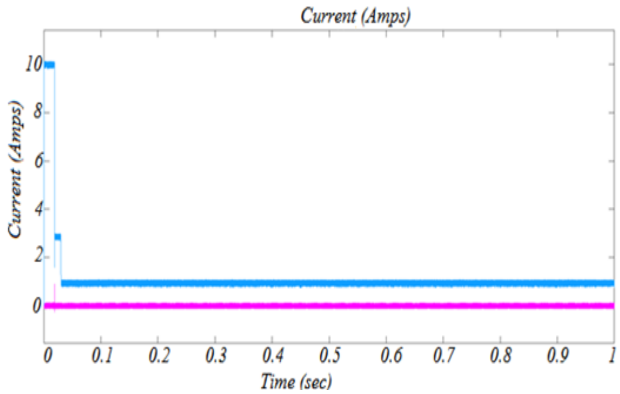


Figure 2.3 dq Current

The above Figure 2.3 shows the simulation result of dq current response of Recurrent Neural network controller based Brushless Direct Current Motor control system.

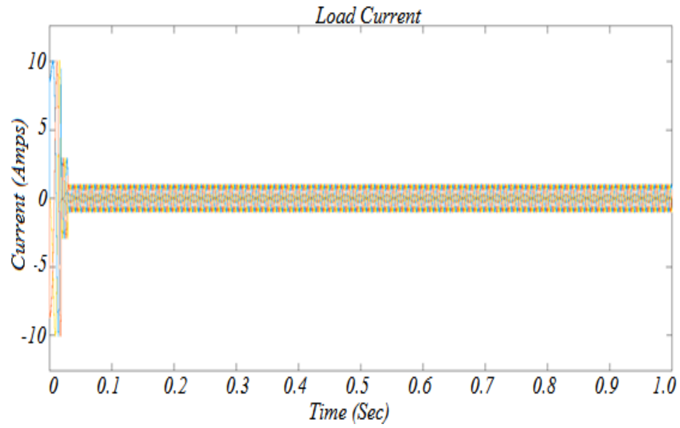


Figure 2.4 Load current

The above Figure 2.4 shows the simulation result of load current response of Recurrent Neural network controller based Brushless Direct Current Motor control system.

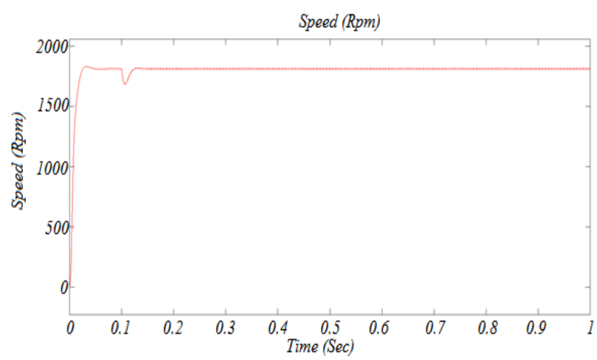


Figure 2.5 Speed

Figure 2.5 shows the speed response during start-up at t=0s, reverse operation at t = 0.2s, then forward operation at t = 0.5s for Recurrent Neural network controller logic 49 rules and 9 rules respectively. Both cases are applied torque load changes at t = 0.9s about 1Nm for motor “1” and 0.5 Nm for motor “2”. For the case of low load, the motors are not too affected by the changes.

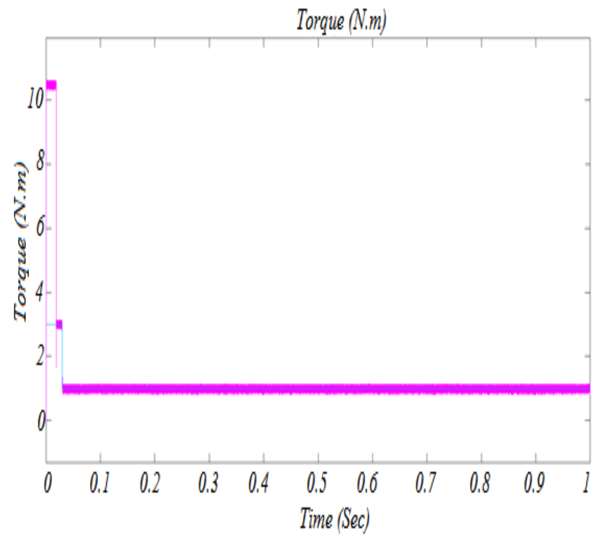


Figure 2.6 Torque

From the simulation comes to fruition, it can be obtained that in steady state, there are swells in torque wave and besides the starting response of the current is high. Moreover to extend the toughness of the motor, and a further more unique speedy reaction can be refined, the proposed torque response has shown up in Figure 2.6

Table 2.2 Comparison results for different load condition

Methods	Peak time(sec)	Reference value(rpm)	Peak Overshoot (%)	Recovery time(sec)	Steady state error value (rpm)	Steady state error (%)
FUZZY	0.6010	1500	1.4151	0.60	9.25	0.82
ANFIS	0.6002	1500	0.9814	0.56	8.1	0.66
RNN	0.8948	1500	0.7414	0.43	6.2	0.46

To Compare the Controller activity with different parameters, for example, rise time, peak time, overshoot and settling time are taken. From the simulation results, the correlation will be organized in table 2.2. The results demonstrate that RNN based controller has less ascent time, settling time and maximum overshoot than a customary controller. The accompanying shortcoming investigation is utilized as a part of the planned request like that voltage, current, enduring state error, FFT and THD checking

III. CONCLUSION

Advantages of the developed system include a continuous monitoring of more and more applications over the industry and control of them even if they exceed their minimum limits. The main focus of this work is bringing out the influence of power converter topologies on the performance of BLDC drive. In this work, utilization of the RNN permits active voltage control of and besides concealment of a particular set of harmonics. The favourable principal position of the proposed technique is that it requires delicate processing switching angles. The scheme was actualized to assess its execution at the disposal of harmonics in Inverter. The monitoring of the BLDC motor system presents the measurement of different parameters, namely settling time, rise time, fall time, peak overshoot and steady state value, voltage and current consumption. The proposed RNN achieves significant result against all parameters like THD level of 5.26%, peak time of 0.8948 sec and steady state error of 0.46%.

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