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ANN WITH LEVENBERG-MARQUARDT BACK PROPAGATION (LMBP) FOR SPEED CONTROL OF THREE PHASE INDUCTION MOTOR DRIVE

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Abstract

In order to manage the speed and torque of an IM drive, this research presents a direct torque control with a space vector pulse width (DTC) technique based mostly on artificial neural networks (ANN). To train the neural network, Levenberg-Marquardt back propagation (LMBP) was employed. Considering how an electric drive performs genuinely based on the speed controller's quality, it is suggested that a neural network controller be used in place of the traditional PID controllers to improve drive performance.

The speed controller's neural network was developed and trained. The neural network controller has evolved and now recognises the need for a speed controller. To evaluate the controller's performance, it was applied within the feed-forward back propagation technique. A multilayer feed forward back propagation a method is employed to train the network and assess its effectiveness. Using the MATLAB/Simulink block programme, a simulation model depicting the entire neural Induction motor driving network-based direct torque control technique using svpwm is created and confirmed.

The outcomes of drive for an induction motor using a space vector pulse with modulator (SVPWM) were contrasted with the outcomes of induction motor drive speed control of ANN fed DTC. Total harmonic distortion (THDTime analysis, including findings from the DTC SVPWMIM and ANNDTCIM models, as well as rising time, delay time, peak time, and overshoot have been performed.

Keywords: Induction Motor (I.M), Direct Torque Control (DTC), Artificial Neural Network (ANN), Levenzberg-Marquardt back propagation (LMBP).Space Vector Pulse Width Modulation (SVPWM).

Introduction : The development of electrical motors drastically altered the way we work, play, and live. It opened the door for widespread electrical use, which is today a need in our daily life. Electrical motors have a long history that dates back to the early 19th century, when scientists firstinvestigate the connection between magnetism and electricity. In 1820, Hans Christian Oersted made the discovery that an electric current has a magnetic effect. This opened the door for more investigation into the characteristics of electricity and magnetism. Michael Faraday made the first crude DC motor a year after discovering electromagnetic rotation. But it wasn't until the late 19th century that widespread use of electrical motors started. In 1883, he took advantage of the idea to create an effective AC motor, which opened the door for the widespread usage of electricity. Electrical motors are employed in a variety of ways today, from driving machinery and equipment in factories and businesses to powering appliances and automobiles. The development of electrical motors over time is a testament to the intellect and inventiveness of the scientists and innovators who have contributed to the development of the modern world.

Artificial Neural Network Model

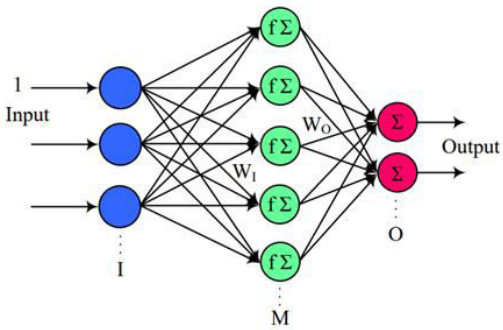

Figure1: Multilayer feed-forward Artificialneural network

Individual neurons can be interconnected in a neural network in order for their outputs to serve as inputs by other neurons. These connections make up the network's layers, which consist of an input layer, one or more hidden layers, and an output layer most frequently. The neural network utilised in this work had one bias neuron with input unity in both the input and hidden layers, and a neuron dedicated to each input to match the typical PI controller. the summarization of the inputs entering the neurons in the cover layer used a nonlinear activation function, such as a sigmoidal function.

$$f(i) = \frac{1}{(1+e^{-i})}$$

IM Drive, an artificial neural network-based speed controller

An effective speed controller that can quickly and precisely track the command speed in various operating scenarios conditions, including variations in system parameters, unanticipated load disturbances, and other factors, is necessary for an induction motor (IM) drive system with great performance. Due to different uncertainties and disturbances including saturation effects, load variations, temperature changes, and noise, conventional controllers require an exact system model of the IM, which is challenging to achieve. In order to get over these difficulties, this work imitates a Use of an artificial neural network in a proportional-integral (PI) controller (ANN).Yet, the ANN-based controller does not need a precise system, in contrast to conventional PI controllers.

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Design of the IM. The ANN is instead trained to provide appropriate fixed weights that enable it to accurately follow the intended speed. Compared to other structures that do not permit such elements, this sort of construction is more effective. In general, the implementation of an ANN-based speed controller in an IM drive system can enhance performance by achieving quick and accurate command speed tracking under diverse operating situations, without necessitating an exact system model of the IM.

Vector Control of the IM Using a Controller for Artificial Neural Networks

The figure depicts the indirect vector control strategy used by the actualized IM drive system. As the system's speed controller, an artificial neural network (ANN) uses inputs for speed of a command and speed errors. Slip is added to the data on rotor speed from the speed sensor on the rotor shaft to determine the rotor position. The input calculator additionally uses phase current data to determine the suitable reference command torque. The command torque produced by the ANN controller is used to create the iqs* component. The constant flux command, which is said to have reached saturation, is used to calculate the ids* component. Current transformations are used to apply the ids* and iqs* components to the motor stator, and then a voltage source inverter is used to apply them to the hysteresis current controller. Overall, the employment of an ANN as the speed controller in this system enables precise control of the IM under varied operating situations. The torque and flux of the motor can be precisely and successfully controlled by utilising an indirect vector control approach.

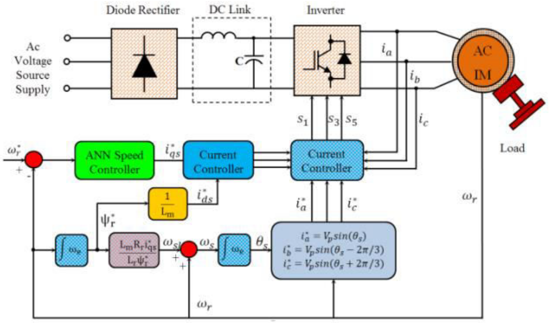

Figure2: Illustration of vector control scheme using ANN

Training Algorithm for Artificial Neural Network

Using an optimisation approach like backpropagation, the weights are modified based on a comparison between the desired output and the ANN's actual output. As long as there is a discrepancy between the desired and actual output is minimised, this process is performed iteratively. The ANN gains the ability to spot patterns and connections between inputs and outputs throughout training. The trained ANN can be used to predict the future or categorise new data once the weights have been improved. The neural network's (ANN) capacity to learn and generalise to new data is influenced by the choice of activation function and neural architecture.

The network can be made nonlinear by using various activation functions, which enables it to describe intricate interactions between inputs and outputs. Similar to this, the network's capacity for learning and generalisation can be impacted by the architecture chosen, including the layer count and number of neurons in each layer. Overall, the quality of an ANN's weights, which are learned through training, as well as the selection of an activation function and neural architecture, have a significant impact on how effectively the ANN performs. The neural network's (ANN) capacity to learn and generalise to new input depends on the choice of activation function and neural architecture.

The network can be made nonlinear by using various activation functions, which enables it to describe intricate interactions between inputs and outputs.Similarly, the choice of architecture, such as the number of layers and neurons in each layer, can affect the network's ability to learn and generalize.

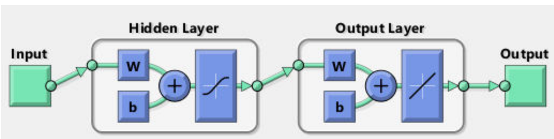

Figure3: Proposed diagram of Based on the Levenberg-Marquardt method, the ANNBack propagation learning algorithm (LM)

The Levenberg-Marquardt algorithm was created with the goal of reducing sum-of-square error functions.

A well-liked substitute for the Gauss-Newton method for determining the minimum of a function that is the sum of squares of nonlinear functions is Levenberg-Marquardt.

$$F(x) = \frac{1}{2} \sum_{i=1}^{m} [f_i(x)]^2.$$

Allowing for the denotation The Levenberg-Marquardt technique then looks in the direction suggested by the solutions of the Jacobian.

$$\left(J_k^{\mathrm{T}} J_k + \lambda_k I\right) p_k = -J_k^{\mathrm{T}} f_k,$$

where is the identity matrix and are nonnegative scalars. The method's appealing feature is that it solves the constrained subproblem of minimising subject to for some scalar linked to.

The command Find Minimum makes advantage of this technique.

$[f, \{x, x0\}]$ when given the Method.

Performance evaluation using Levenberg-Marquardt Algorithm

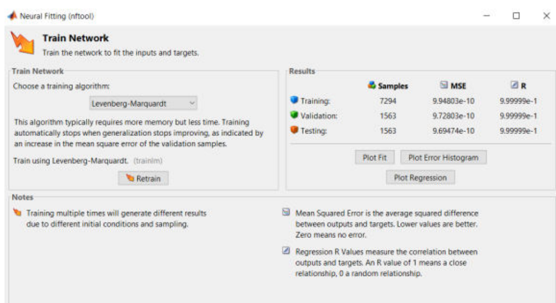

Figure4: Using the Levenberg-Marquardt algorithm to evaluate performance

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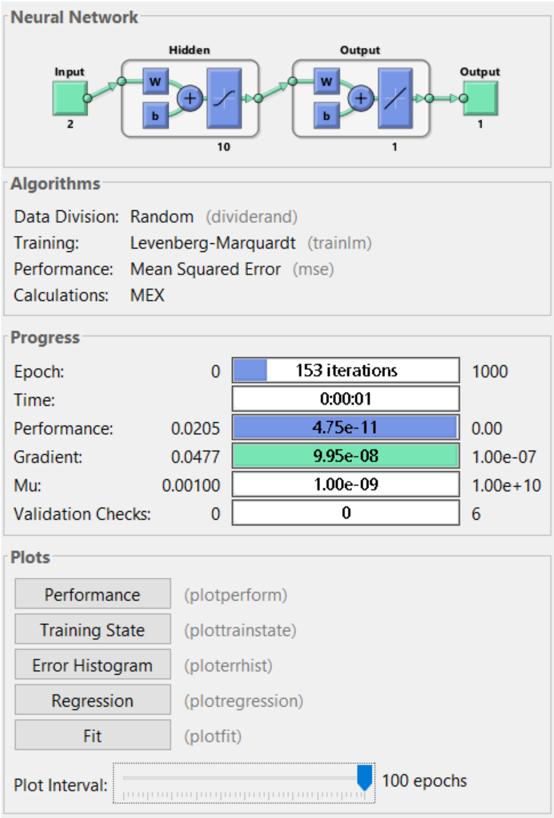

Figure5: Using the Levenberg-Marquardt back propagation algorithm, train neural networks

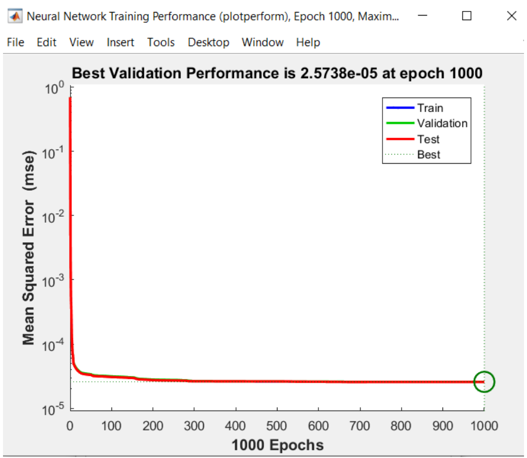

Figure6: Performance of Levenberg-Marquard Backpropagation Algorithm

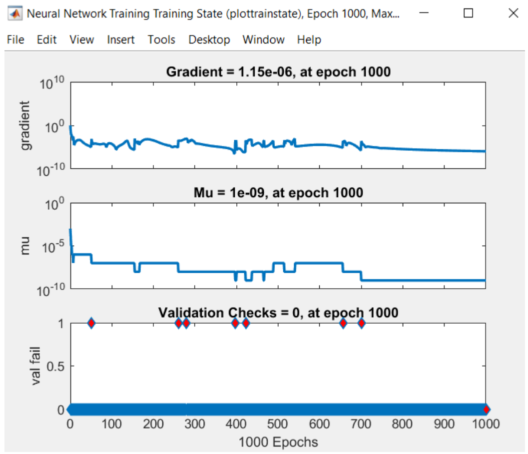

Figure7: LevenbergMarquardt Backpropagation Algorithm Training state and Performance Plot

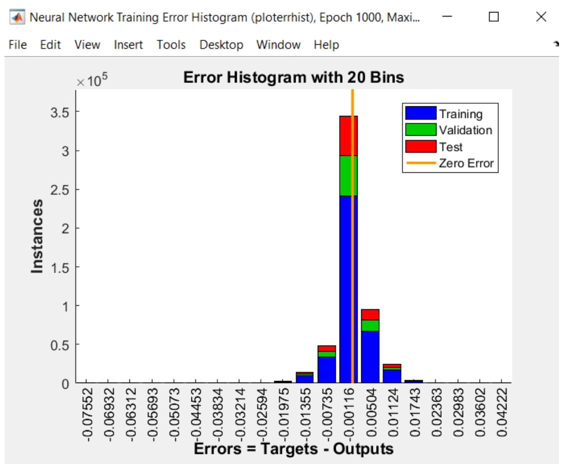

Figure 8: Error Histogram for the nndtc I.M drive fed by the svpwm

The "R" metric, which measures how closely the actual values match the projected values,is used to assess the model's performance. The "R" metric, which measures how closely the To evaluate the model's accuracy, compare the anticipated and actual values. performance. Iterative and frequently used for resolving non-linear least-

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squares issues, the technique is a crucial tool for data-fitting applications in a variety of domains. After training the algorithm for 1000 epochs on the provided dataset, it was successful in your situation in terms of performance.

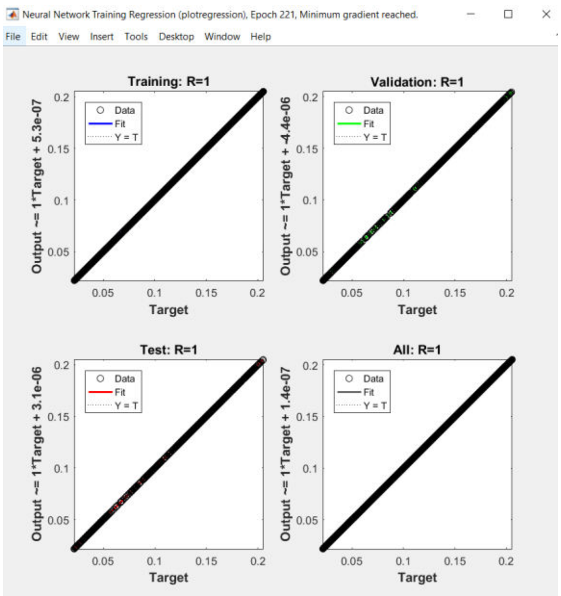

Figure 9: Levenberg-Marquardt Backpropagation Algorithm Regression Analysis Plot

Induction motor (IM) drives that use space vector pulse width modulation (SVPWM) are described in the study as Levenberg-Marquardt backpropagation is used. optimisation algorithm to improve the traditional Direct Torque Control (DTC). Although having more processing demands, The outcomes demonstrate the efficiency of the Marquardt method. for training networks with a few hundred weights. When high precision is crucial, the enhanced efficiency is very advantageous, and the algorithm performs better in terms of convergence than other optimisation techniques. The Marquardt technique is quite effective for training networks with up to a few hundred weights, according to the findings of the article.

The Marquardt algorithm's improved efficiency makes up for the fact that each iteration of the algorithm requires more computing than other optimisation techniques do. When high accuracy is required, this is particularly true.

In conclusion, the text implies that the Levenberg-Marquardt backpropagation optimisation algorithm is a useful technique for enhancing the performance of the standard Drives for induction motors with direct torque control using space vector pulse width modulation, particularly where precision is essential. Although having higher processing requirements, the technique can handle networks with up to a few hundred weights and offers improved efficiency.

Simulink model

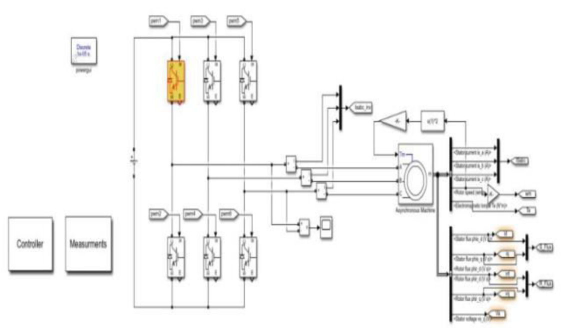

Figure10:Demonstrates a matlab/ simulink model of a neural network controller for an induction motor with direct torque regulation.

Result

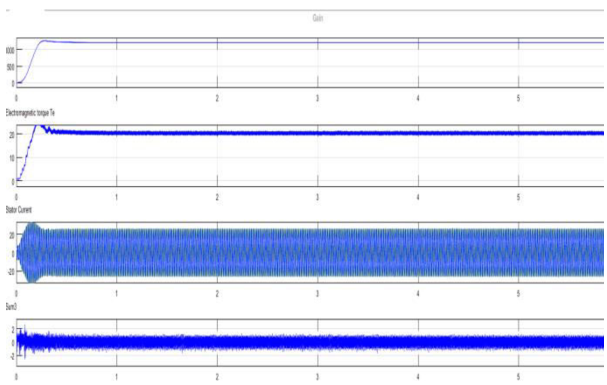

Figure11: Shows the graph of gain,Electromagnetic Torque,Stator current.

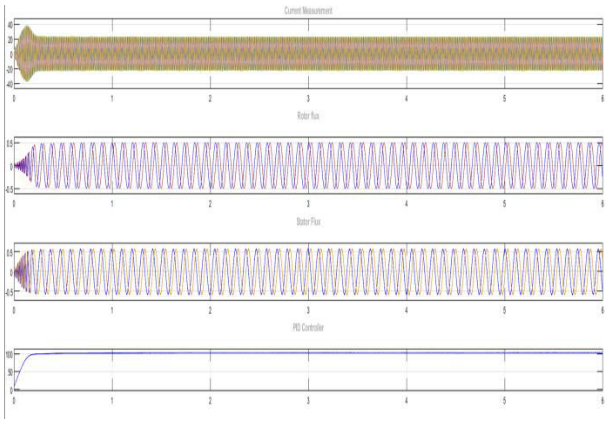

Figure 12: Shows the graph of Rotor flux,Stator flux ,PID controller.

CONCLUSION

Simulated matlab/simulink models have been used to regulate the speed of an Using a neural network controller, an induction motor is operated with direct torque control, sinusoidal pulse width modulation, space vector modulation, and direct torque control.. Figures are used to compare Simulink model outcomes. Simulated matlab/simulink models have been used to regulate the speed of an An induction motor using a neural network controller with direct torque control, sinusoidal pulse width modulation, space vector modulation, and direct torque control. Figures are used to compare Simulink model outcomes

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