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ANN based Torque estimation and Control of induction Motor drive used in Chocolate Industry

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Abstract

The paper focuses mainly on ANN based estimator (to select suitable IM according to load profile) and controller (as future work), and effort will be given to prove that this technique to estimate and track the torque accurately and fast as compared to latest available DSP estimator and other conventional controllers. With the experimental setup (vector control technique) available in lab (in which DSP TMSLF 2407 technology has been implemented for firing of IGBTs and estimation of parameters) set of values will be generated for the parameters v_{ds} v_{qs} i_{ds} i_{qs} θ . Approximately 66000 values will be taken for each parameter. They will be fed to two ANN based estimator and T_e estimated from there will be compared with T_e estimated from DSP control board and it will be shown that ANN estimation technique gives better performance as compared with DSP estimation technique. Also the various parameters taken will also be compared and cross – checked with a vector control simulation model available in MATLAB 6.5.

Introduction

This paper analyses, develops and implements a very fast on-line parameter estimation algorithm for a rotor flux oriented induction motor drive, with the best possible convergence results using ANN. The thesis focuses mainly on ANN based estimator and controller design (as future work), those were found to estimate and track the torque accurately and fast under constant load and constant speed conditions. The rotor flux of the induction motor estimated with a classical voltage model was the key input of the torque estimator. A new estimator using an ANN was found to be much superior to the DSP estimators, both in terms of dynamic estimation times and convergence problems. The torque estimator developed for this thesis used two feed-forward neural networks. Both networks exhibited excellent learning capabilities. The main justifications for application of the methodology are as follows: the thesis contributes to verify if a specific motor is overestimated or underestimated for a certain application as well as the use of the neural approach can also contribute to avoid the increase of energy consumption and power factor, which are caused by overestimated motors, and to avoid still overheating in induction motors working underestimated. Different industries have different requirements, so one type of drive is not suitable for other industry. Few industries with their properties and preferences are listed below, according to which we prefer or we look to design the drives.

About chocolate manufacturing

Flow chart for chocolate manufacturing processes



Figure 1: Flow chart for different processes involved in chocolate production

Scope of the study & limitation

Scope

We have the setup available for vector control of induction motor (DSP used for gate triggering and IM parameter estimation) which is now a days used in many industries, as well as simulink model is also available in MATLAB 6.5. ANN models are also available in MATLAB. With these three modes available we can have an opportunity to get a wide range of datasheet for performance comparison as well as cross-checking also. The latest hardware setups available with vector control technique, i.e with DSP estimation technique; we have the following result for torque,

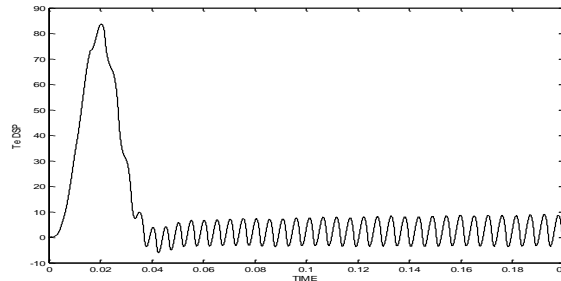


Figure 2: Torque plot from DSP estimation

In this thesis an attempt is made for betterment of this torque plot with ANN estimation technique, focused for getting an error between the desired and actual output in a margin of .001. In this attempt I have achieved the result discussed in figure shown below.

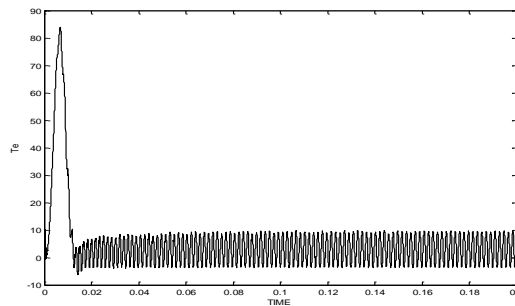


Figure 3: Torque plot from ANN estimation

The ANN based estimator outputs are compared with the corresponding outputs of DSP based estimator and shows good accuracy, fast response and ANN based estimator also showed harmonic-immune performance.

Limitation

After having a lot of effort, for training of ANN block we got the desired error level of .001 in 120 epochs and in the training of ANN block 2 this was .01 in 500 epochs. One another limitation we are facing is with hardware compatibility while we go for ANN training. The requirement for fast training response is at-least Intel® Core(TM)2 Duo CPU T8100 @ 2.10 GHz with 795 MHz, 4 GB RAM or higher configuration.

Details of techniques and equipment employed

Application of ANN for feedback signal estimation (Theory)

Figure 3.17 shows the block diagram of a vector – controlled IM drive where a feed-forward neural network based estimator estimates the rotor flux, unit vector, and torque. In this thesis the estimation of torque only is required. Estimation is done based on the equations discussed above.

A DSP based estimator is also shown in the figure for comparison. Since the FF network cannot solve any dynamic system, the machine terminal voltages are integrated by a hardware low pass filter (LPF) to generate the stator flux signals. The variable frequency, variable magnitude sinusoidal signals are then used to calculate the output parameters by a feed-forward network. Figure 5 shows the topology of the network where there are three layers, and the hidden layer contains 20 neurons.

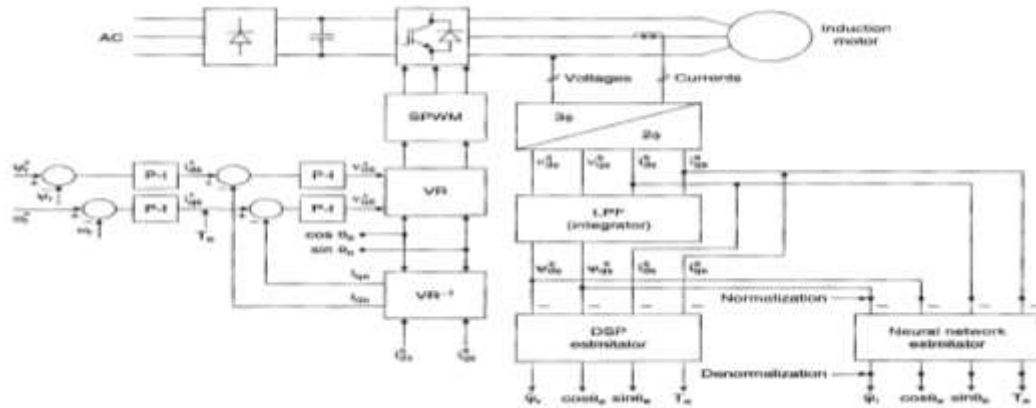


Figure 4: Vector – controlled IM drive with neural network – based estimator

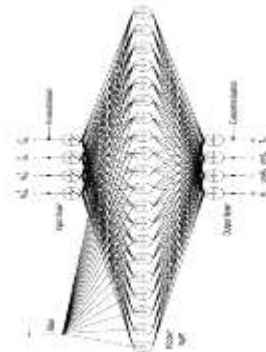


Figure 5: Neural network topology (4-20-4) for estimation

The input layer neurons have linear activation characteristics (or else, no activation functions), but the hidden and output layers have a hyperbolic tan – type activation function to produce bipolar outputs. Figure x.x shows the torque, flux, and unit vector signals of the estimator after successful training of the network with a large number of simulation data sets. The estimator outputs are compared with the corresponding outputs of the DSP based estimator and show good accuracy. When tested with a low switching frequency of the inverter (2 kHz instead of 15kHz), the ANN based estimator showed somewhat harmonic – immune performance. Inherent noise or harmonic filtering is one of the advantages of a neural network.

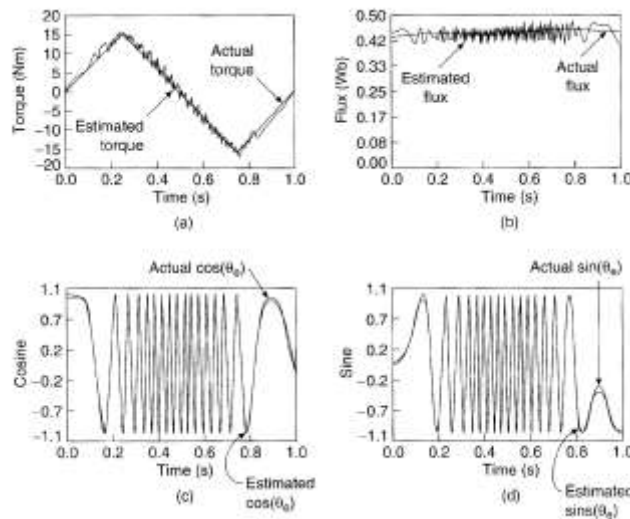


Figure 6 ANN based estimator performance (a) Torque, (b) Rotor flux, (c) $\cos \theta_e$, (d) $\sin \theta_e$

Proposed ANN structure for torque estimation [7]

Back propagation (BP) neural network structure is used for estimation of vector controlled induction motor parameter such as torque, speed and flux magnitude and position, because BP network each unit receives inputs from preceding layer. The significance of this is that the information going into the hidden layer units recorder into an internal representation and outputs are generated by internal representation rather than by inputs. The input signals are then converted in by the ANN according to the connection weights. In learning process, connection weight update in a direction to minimize error between desired outputs and ANN outputs. These errors are then back-propagate. Rotor flux and position are estimated using single ANN structure and given better result but contain more harmonics compare to two ANN Structure. The rotor flux and position are also estimated using two ANN, one for estimated rotor flux and other estimated rotor position also contain more harmonics. In this topic I proposed two ANN structure, one ANN structure estimated stator d-axis and q-axis flux and the second ANN structure estimated rotor d-axis and q-axis fluxes. Rotor flux and position is estimated using equation for estimation discussed above.

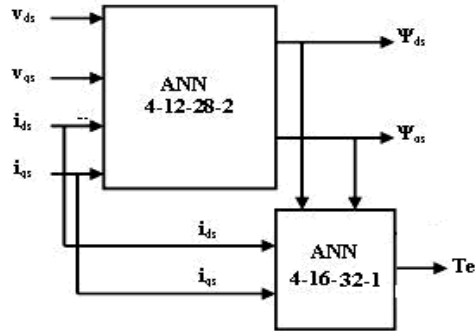


Figure 7: Block diagram of proposed ANN structure

The block diagram of proposed ANN structure shown in figure above, the first ANN Structure consist 4 layer (4-12-28-2) used tansin and purelin as activation function and Levenberg-Marquardt algorithm used for training data, data train upto 120 epochs and mean square error is 0.001 at learning rate is 0.04 and estimate stator d-axis and q-axis fluxes. The Second ANN structure also consist 4 layer (4-16-32-2) using ‘tansin and purelin as activation functions and Levenberg-Marquardt algorithm is used for training data, the maximum iteration is taken as 500 epochs and target mean square error is 0.001 at learning rate of 0.04 to estimate load torque. Input-output training 50,000 data may be generated by using TMSLF 2407 DSP controller with the help of Intelligent power module and also by simulation model.



Figure 8: TMSLF 2407 DSP

Proposed Simulink model for “simulated data generation”

Here, step by step procedure is given,
Changing parameters of induction motor according to lab setup

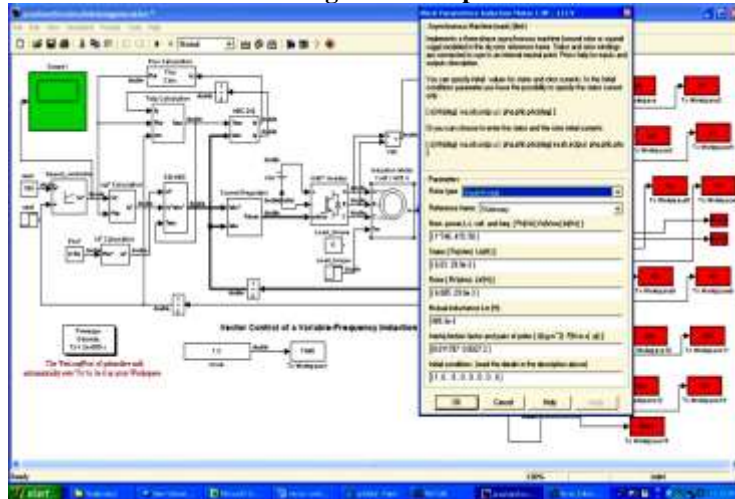


Figure 9: Changing parameters of induction motor

Changing inverter parameters according to lab setup

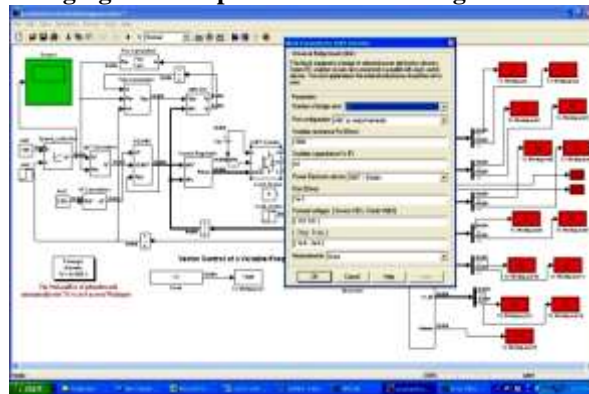


Figure 10: Changing inverter parameters

Determining IM parameters to workspace for data generation

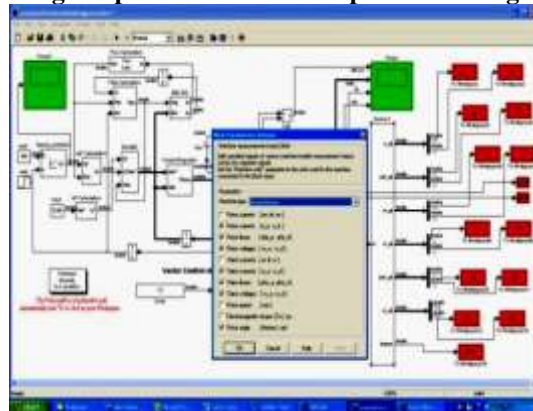


Figure 11: Determining IM parameters to workspace

Complete circuit for simulation

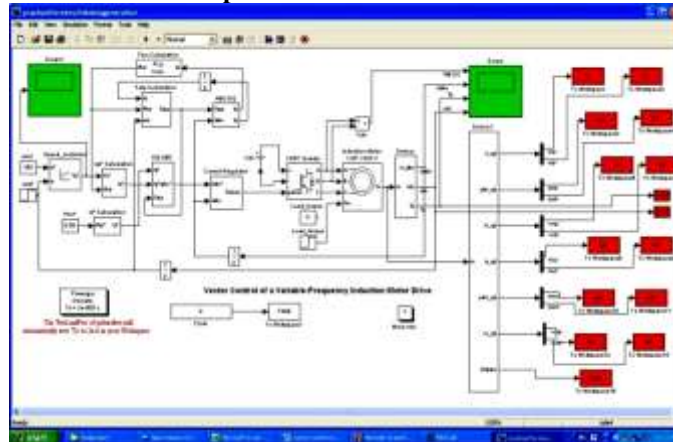
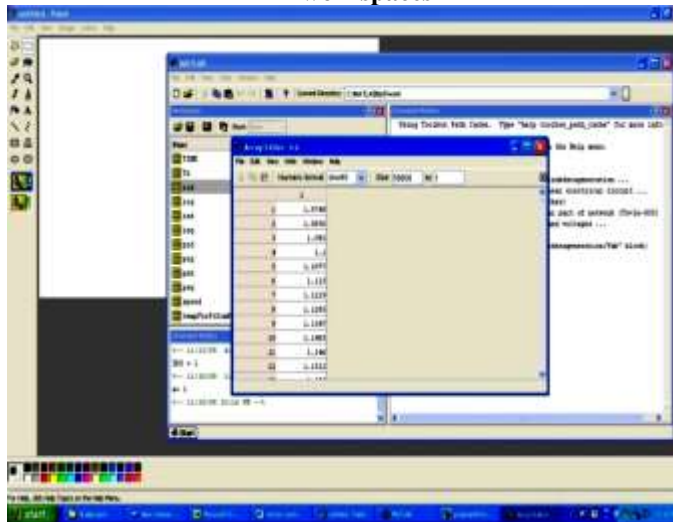


Figure 12: Complete circuit for simulation
All workspaces



Sample array editor for I_{rd}



Figure 14: Sample array editor for I_{rd}

Graphs from DSP Estimation model [4]
Waveform generated for stator direct axis flux ψ_{ds}

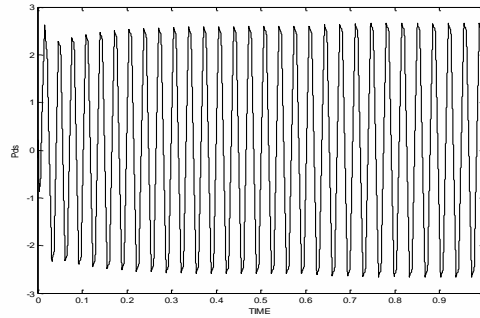


Figure 13: All workspaces

Figure 15: Waveform generated for stator direct axis flux ψ_{ds}

Waveform generated for stator quadrature axis flux ψ_{qs}

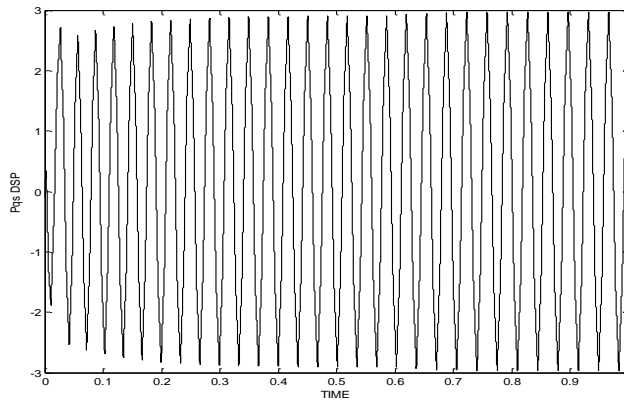


Figure 16: Waveform generated for stator quadrature axis flux ψ_{qs}

Waveform generated for torque

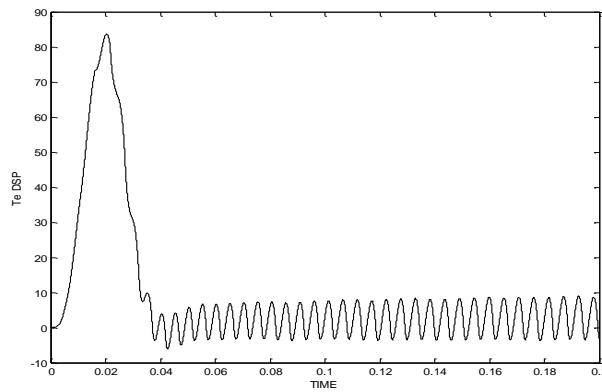
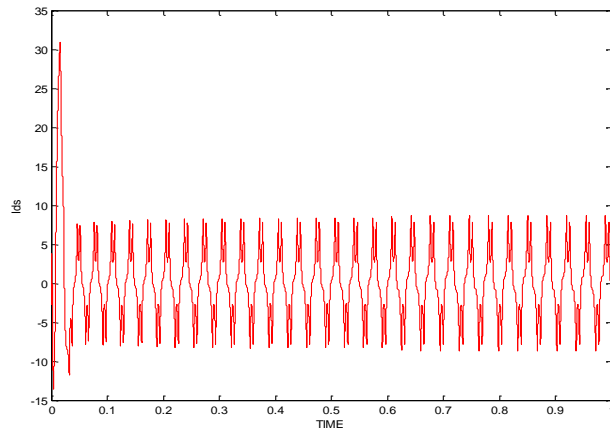


Figure 17: Waveform generated for Torque
Waveform generated for I_{ds}



**Figure 18: Waveform generated for Ids
Waveform generated for Iqs**

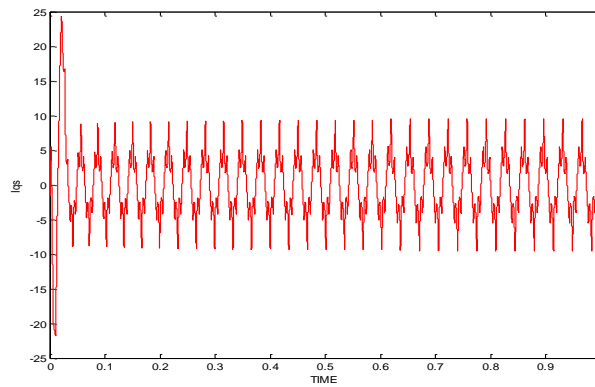
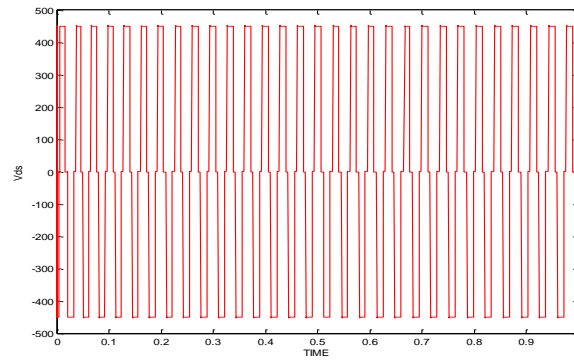


Figure 19: Waveform generated for Iqs

Waveform generated for Vds



**Figure 20: Waveform generated for Vds
Waveform generated for Vqs**

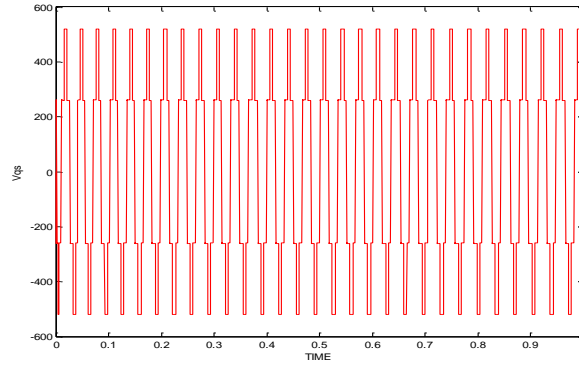


Figure 21: Waveform generated for Vqs

Datasheets from ANN Model
Output from ANN block 1: ψ_{ds} and ψ_{qs}



Figure 22: Outputs form ANN block 1.

Output from ANN block 2: T_e

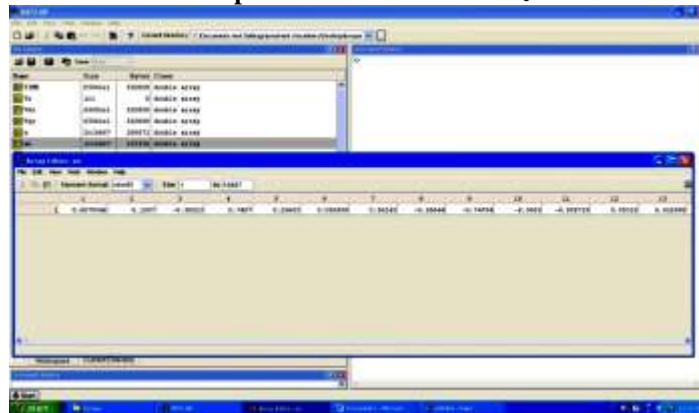


Figure 23: Output from ANN block 2.

Graphs from ANN model [4]
Waveform generated for stator direct axis flux ψ_{ds}

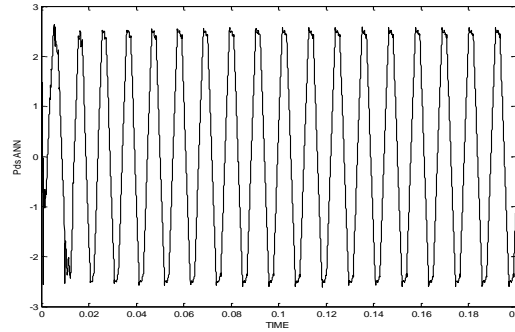


Figure 24: Waveform generated for stator direct axis flux ψ_{ds}

4.6.2 Waveform generated for stator quadrature axis flux ψ_{qs}

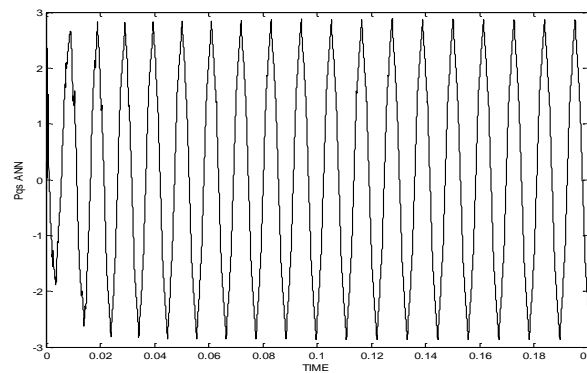


Figure 25: Waveform generated for stator quadrature axis flux ψ_{qs}
Waveform generated for torque

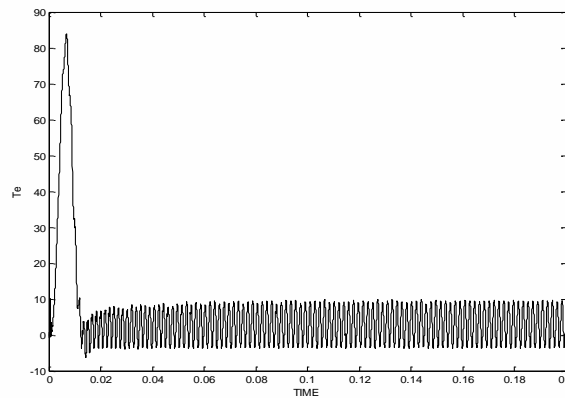


Figure 26: Torque waveform from ANN estimation model

Comparison ψ_{ds} (DSP estimation) Vs. ψ_{ds} (ANN estimation)

Fig. 27 shows, estimated value of stator d-axis flux at 3-N-m load and change after 0.6 second to 6-N-m load torque. The ANN based d-axis flux and DSP based d-axis flux reach peak value of 2.5 pu at the same time of 0.01sec. In the case of ANN based estimator, the peak value of flux is maintained constant throughout the operation, and its value is more as compare to DSP based estimated peak value of 2.48 pu.

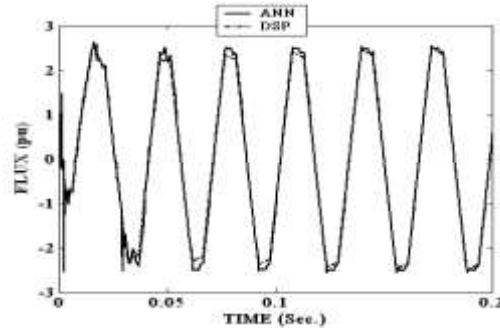


Fig.27: Stator d- axis flux comparison

Comparison ψ_{qs} (DSP estimation) Vs. ψ_{qs} (ANN estimation)

Fig. 28 shows the stator q-axis flux at load torque of 3-N-m load and change after 0.6 sec to 6-N-m load torque. ANN based estimation of stator q-axis flux and DSP based estimation of flux reach the peak value of 2.8 pu after 0.02 sec. Both the estimated values have close resemblance but ANN based peak flux (2.8 pu) is slightly higher than DSP based peak flux of 2.74 pu.

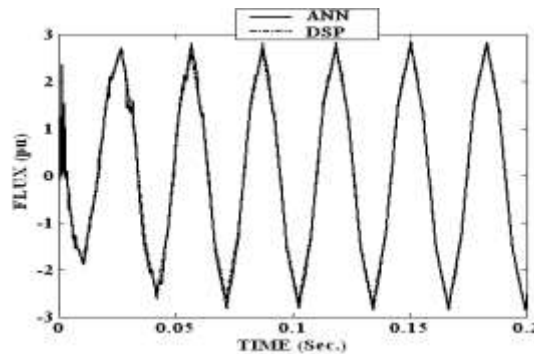


Fig.28: Stator q- axis flux comparison

Comparison T_e (DSP estimation) Vs. T_e (ANN estimation)

The load torque estimation using ANN estimator and DSP estimator is shown in fig 29. The average estimated value of load torque is 3-N-m upto time 3 Sec. after that its average value is 6-N-m. at light load 3-N-m both estimator follows same tracks as load increases 6-N-m ANN estimator estimate peak value of load torque is 11.8 N-m while DSP estimated value was found to be 11.4 N-m. The ANN based estimator outputs are compared with the corresponding outputs of DSP based estimator and shows good accuracy, fast response and ANN based estimator also showed harmonic-immune performance.

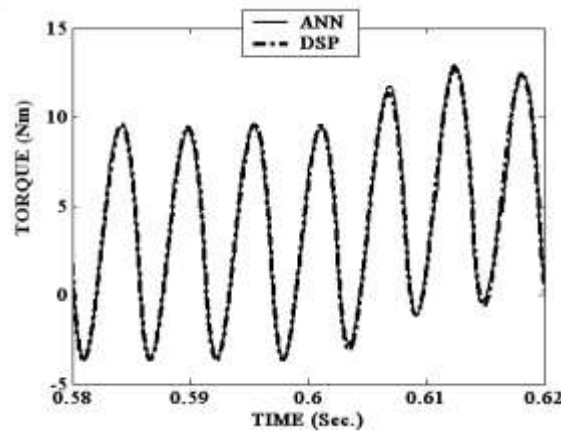


Fig. 29: Torque comparison

Conclusion

This paper has described a vector-controlled induction motor drive that incorporates a feedforward neural-network for estimation of rotor flux and position and torque. For ANN Simulations, using MATLAB Software Package, have been carried out to verify the effectiveness of the proposed method. Flux reference is set to its rated value of 2.4 pu, speed reference is set from 0 to 150 rad/s, and the load torque is varied 3- Nm to 5-Nm at 1.3 s. The paper successfully demonstrates the application of ANN in the estimation of rotor flux and position for a vector controlled induction motor drive system. A four-layer feedforward neural network of the structure four-twelve- twenty eight – two thirteen-two has been trained, for estimation of stator d-axis and q- axis flux and the performance of the neural net estimator is found to be excellent in comparison to DSP based estimator. Also an another four-layer feedforward neural network of the structure four-sixteen- thirty two – one has been trained, for estimation of axis flux and the performance of the neural net estimator is found to be excellent in comparison to DSP based estimator.

Suggestions for future research work

During the research work it was seen that during the estimation process an error of nearly 1% is coming out. The future work will be for the reduction of this error as well as to develop an scheme for torque tracking by ANN as well as Fuzzy – Logic concept.

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