Stator Current Drift Compensation in Vector Controlled Induction Motor Using Auto-Associative Neural Network

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ABSTRACT
In this paper, sensor drift compensation of vector control of induction motor using neural network is presented. An induction motor is controlled based on vector control. The sensors sense the primary feedback signals for the feedback control system which is processed by the controller. Any fault in the sensors cause incorrect measurements of feedback signals due to malfunction in sensor circuit elements which affects the system performance. Hence, sensor fault compensation or drift compensation is important for an electric drive. Analysis of sensor drift compensation in motor drives is done using neural networks. The feedback signals from the phase current sensors are given as the neural network input. The neural network then performs the auto-associative mapping of these signals so that its output is an estimate of the sensed signals. Since the Auto-associative neural network exploits the physical and analytical redundancy, whenever a sensor starts to drift, the drift is compensated at the output, and the performance of the drive system is barely affected.

Keywords
Auto Associative Neural Network (AANN), Induction Motor, Vector control, Sensor Drift Compensation.

1. INTRODUCTION
A drive system basically consists of an electric machine, a converter, primary sensor for feedback signal, feedback signal estimator and system controller. The sensors are extremely important in a drive system or any other feedback control system because primarily all control algorithms are based on measurements. The sensor faults cause incorrect measurement of feedback signals due to malfunction in the transducers and sensor circuit elements and upsets the system performance [2]. This paper proposes the use of Auto Associative neural network to compensate the drift problem in feedback current sensors in a vector controlled induction motor drive.

Scalar control involves controlling only the magnitude of the control variables with no concern for the coupling effects between these variables. Conversely, vector or field orientated control involves adjusting the magnitude and phase alignment of the vector quantities of the motor. Scalar control, such as the Constant Volts/Hertz method when applied to an AC induction motor is relatively simple to implement but gives a sluggish response because of the inherent coupling effect due to torque and flux being functions of current and frequency. Vector control de-couples the vectors of field current and armature flux so that they may be controlled independently to provide fast transient response [1]. Accurate position control is not possible with scalar control since this requires instantaneous control of the torque. This requires either, instantaneous change to the stator currents, which is not possible due to energy storage effects, or instantaneous change to the rotor current which in the case of scalar control is controlled indirectly via the stator currents. Similarly, whilst scalar control may provide acceptable steady state speed control, precise and responsive speed control due to load changes requires accurate and responsive torque control. The vector approach overcomes the sluggish transient response when using scalar control of AC motors [7].

2. VECTOR CONTROL
Vector control of an Induction motor is also called Field orientation control. In a typical AC induction motor, three alternating currents electrically displaced by 120◦ are applied to three stationary stator coils of the motor. The resulting flux from the stator induces alternating currents in the 'squirrel cage' conductors of the rotor to create its own field these fields interact to create torque. Unlike a DC machine the rotor currents in an AC induction motor can not be controlled directly from an external source, but are derived from the interaction between the stator field and the resultant currents induced in the rotor conductors [13]. Vector control of an AC induction motor is analogous to the control of a separately excited DC motor [7]. In a DC motor the field flux ψ_f produced by the field current I_f is perpendicular to the armature flux ψ_a produced by the armature current I_a . These fields are decoupled and stationary with respect to each other. Therefore when the armature current is controlled to control torque the field flux remains unaffected enabling a fast transient response (see Figure 1).

In a vector-controlled drive, the machine stator current vector I_s has two components: i_{ds} or flux component and i_{qs} or torque component, as shown in the phasor diagram. These current components are to be controlled independently, as in a dc machine, to control the flux and torque, respectively. The i_{ds} is oriented in the direction of ψ_r, and i_{qs} is oriented orthogonally to it. The controller should make the two inverse transformations,

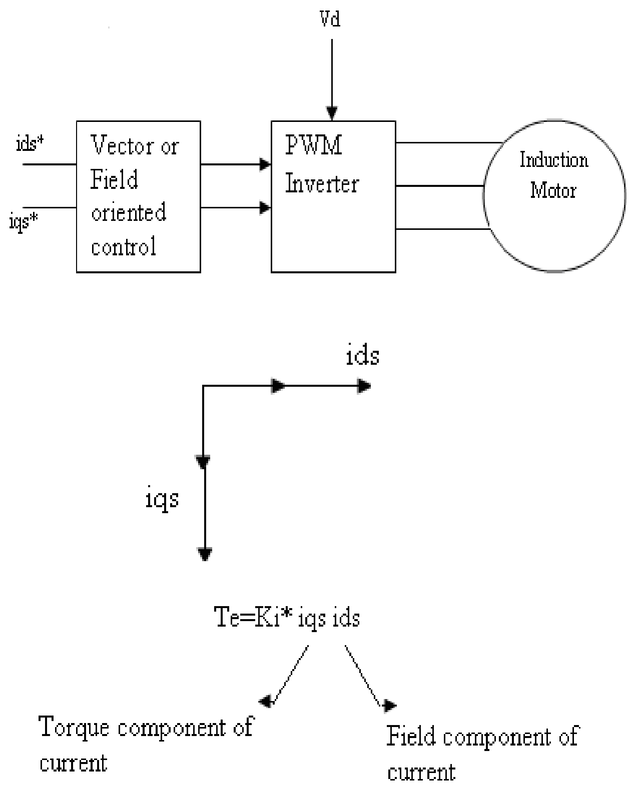

Figure 1 Vector control of Induction motor

where the unit vector $\cos\theta_e$ and $\sin\theta_e$ in the controller should ensure correct alignment of i_{ds} in the direction of ψ_r and i_{qs} at 90◦ ahead of it. Obviously, the unit vector is the key element for vector control [8].There is two methods of vector control depending on the derivation of the unit vector. These are the direct (or feedback) method and indirect (or feed forward) method. For closed-loop flux control in constant-torque and field weakening regions, i_{ds} can be controlled within the programmed flux control loop so that the inverter always operates in PWM mode[1] .

2.1 Stator flux oriented Vector control

The phasor diagram below (Figure 2) explains stator oriented vector control, where i_{ds} is oriented in the direction of V_s and i_{qs} is perpendicular to it. One advantage of stator orientation is that the estimation of the flux and the corresponding unit vector is more accurate because only stator resistance variation affects the accuracy.

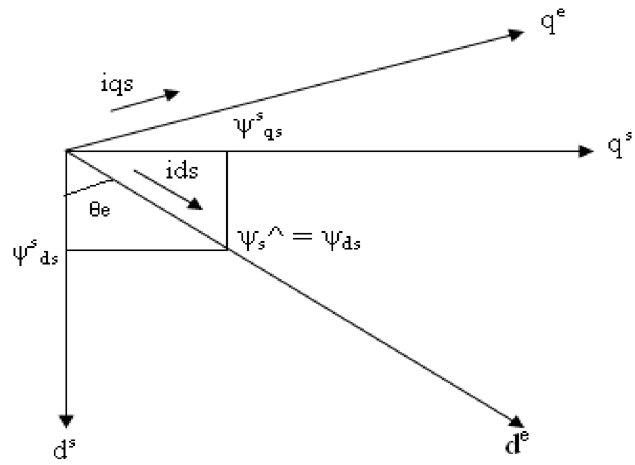

Figure 2 Phasor diagram of stator flux vector control

3. DRIVE SYSTEM

It has been established that i_q and i_d of the rotating reference frame must be controlled to provide good dynamic control of the induction motor. Using closed loop control ordered quantities of i_q and i_d are compared with the actual values measured from the motor. In order to obtain the motor values we have to perform transformations on the measured 3 phase stator currents into the direct and quadrature components of the rotating reference frame. The resulting error terms are then transformed back to 3 phase quantities and applied to the motor.

The power circuit (Figure 3) consists of a DC source (battery or rectifier DC), PWM IGBT inverter and cage type induction motor. The signal processing blocks include machine phase current sensors, signals computation and controller, and the PWM algorithm [3]. The command torque (T_{e*}) and stator flux (ψ_{s*}) generate the active (i_{qs*}) and reactive (i_{ds*}) current commands within the block which are then translated to generate input for PWM controller.

The machine terminal voltages and currents are sensed and converted into stationery frame $d_s - q_s$ signals. These signals are then converted to rotating frame. The synchronous control loops then generate V_{qs*} and V_{ds*} signals. V_{qs*} and V_{ds*} signals are then translated using inverse Clarke transformation and fed as input to PWM controller. The PWM controller receives signals at the input and translates to gate drive signals for the IGBT inverter [8].

4. AUTOASSOCIATIVE NEURAL NETWORKS

Artificial neural network is a system of interconnecting neurons in a network working together to produce an output function.

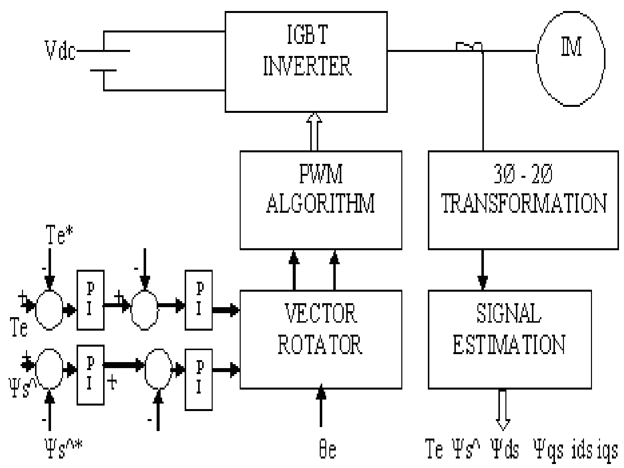

Figure 3 Block diagram of Vector control of Induction motor

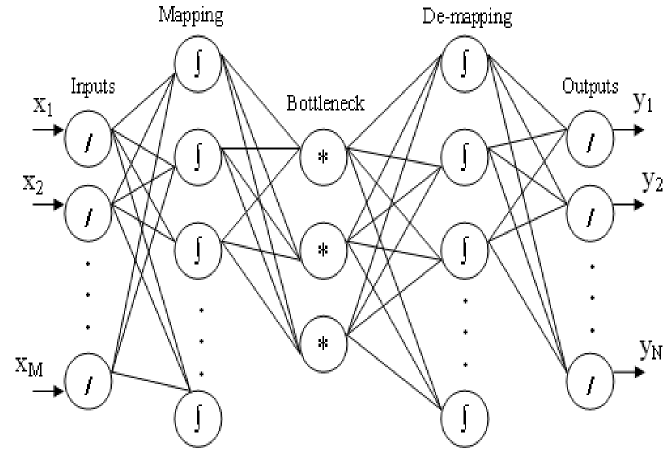

Figure 4 Architecture of AANN

The output of neural network relies on the cooperation of the individual neurons within the network to operate. A unique property of neural network is that it can still perform its overall function even if some of the neurons are not functioning. Associative memory neural nets are single layer nets in which the weights are determined in such a way that the net can store a set of pattern associations. In an input - output vector pair 's:t' ,if each vector 't' is same as vector 's' with which it is associated , then the net is called auto associative net. An auto- associative neural network (AANN) is a class of artificial neural network (ANN) in which the outputs are trained to emulate the same as the inputs over an appropriate dynamic range. The AANN concept can capture the relationship between input and output signals that have some degree of relation with each other [6].

Many plant variables that have some degree of coherence with each other constitute the inputs. For an auto associative net the training input and target output vectors are identical. During training, in order to make each output equal to the corresponding input, the interrelationship between the variables is embedded in the connection weights. A stored vector can be retrieved from distorted or partial input if the input is sufficiently similar to it. Auto-associative neural network is basically a feed forward, fully-connected, multilayer perceptron (MLP) type neural network. The AANN architecture (Figure 4) contains an input layer, a number of hidden layers and an output layer [10]. Three hidden layers are theoretically enough for an AANN.

No. of neurons in input layer = 3

No. of neurons in mapping layer = 8

No. of neurons in bottleneck layer = 2

No. of neurons in de-mapping layer = 8

No. of neurons in output layer = 3

However, additional hidden layers may improve the performance of the model and help to more effectively map the interrelationship among variables. The first hidden layer is called the Mapping layer. The transfer function of the nodes in the Mapping layer can be sigmoid or other similar nonlinear functions. The second hidden layer is called the Bottleneck layer which is responsible for the auto-association of signals. The dimensionality of the Bottleneck layer is the smallest one in the network and its transfer function can be linear or nonlinear. However, the transfer function of both input and output layers is linear. The third or last hidden layer is called the De-Mapping layer whose nodal transfer functions are nonlinear as indicated. The Mapping and De-Mapping layers have more neurons than the input and output layers.

The whole network can be considered as cascaded connection of two three-layer sub-nets, where the signals are compressed in the Bottleneck layer. The AANN can be trained with example data using the standard back propagation method. The network is characterized by one-to-one mapping between the input and the output signals. During training, the Bottleneck layer forces the AANN to encode or compress the input signals and then decode or decompress them to restore the network outputs. As a result, any specific output shows virtually no change when the corresponding input pattern has been distorted by noise, missing data, or nonlinearity [11]. This characteristic allows the AANN to detect drift or failure by comparing the sensor output with the corresponding network estimate.

5. SIMULATION STUDY

To implement an auto associative neural network for sensor drift compensation multiplicative and additive errors were implicated in the stator part of the induction motor. Stator currents were observed for different values of errors to obtain the training data (Table 1) for neural network.

Table 1 Sample training data for neural network

S.No.	Error factor	Input			Output		
		Ia	Ib	Ic	ia	ib	ic
1)	0.05	0.9	20	20	20	20	20
2)	0.1	1.9	20	20	20	20	20
3)	0.15	2.9	20	20	20	20	20
4)	0.1	1.5	15	15	17	17	17
5)	0.5	8	15	15	17	17	17
6)	0.7	4.5	15	15	17	17	17
7)	0.4	18	7	19	18	18	18
8)	0.6	19	19	10	18	18	18
9)	0.5	9.2	19	18	19	19	19
10)	0.1	2.1	21	20	21	21	21
11)	0.2	21	4	21	21	21	21
12)	0.5	11	22	21	22	22	22
13)	0.7	22	16	22	22	22	22
14)	0.9	22	21	20	22	22	22
15)	0.1	3	23	21	23	23	23
16)	0.5	23	12	23	23	23	23
17)	0.6	23	21	14	23	23	23
18)	1.5	16	19	19	20	20	20
19)	-1.5	16	19	19	20	20	20
20)	2	17	19	19	20	20	20

The corresponding stator currents are shown in Figure 5 and 6. By introducing different errors in Matlab Simulink, 335 sets of training data were obtained. Using this data the auto-associative neural network with back propagation algorithm was trained with 5 layers.

Figure 5 shows the original stator current values obtained with Vector control of Induction motor. Figure 6 indicates the reduction in stator current due to fault in phase A

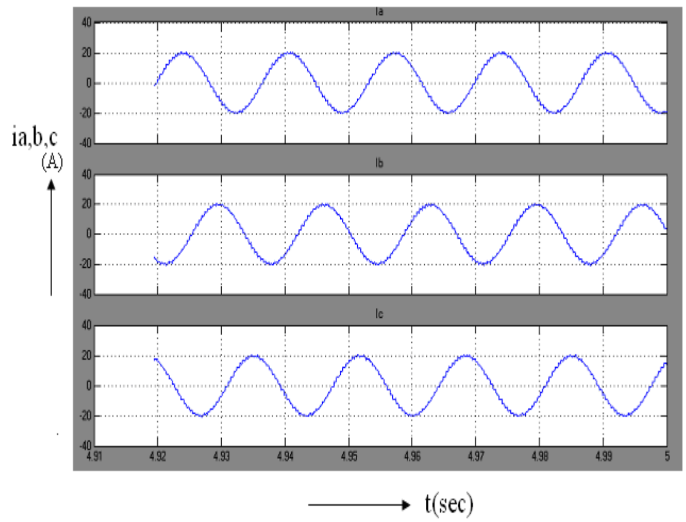

Figure 5 Stator currents (ia,ib,ic)

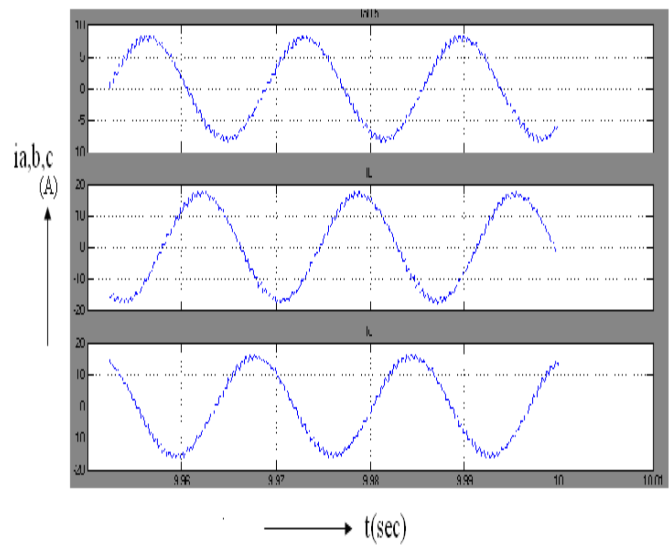

Figure 6 Reduced Stator currents with implicated error

.6. RESULTS

Vector control of Induction motor was simulated using Matlab Simulink and three stator currents i_a, i_b, i_c were noted. Multiplicative and additive errors were implicated in the stator currents to obtain the training data for neural network. The Auto associative neural network adopting backpropagation algorithm was trained and tested. With every successive iteration the cumulative root mean square error in the network (target – output), was found to reduce. Figure 7 gives the error versus iteration graph. As the number of iterations continues to increase the cumulative mean square error for 335 sets of data was found to reduce. The lowest root mean square error obtained was 11.93 for a complete 335 set of data. The number of neurons in each of the layers was determined using trial and error method with approximately 50,000 iterations. The satisfactory output was obtained for the layer with neurons 3 – 8 – 2 – 8 – 3. (Input – Mapping – Bottleneck – Demapping – Output). Auto-associative neural network with back propagation algorithm

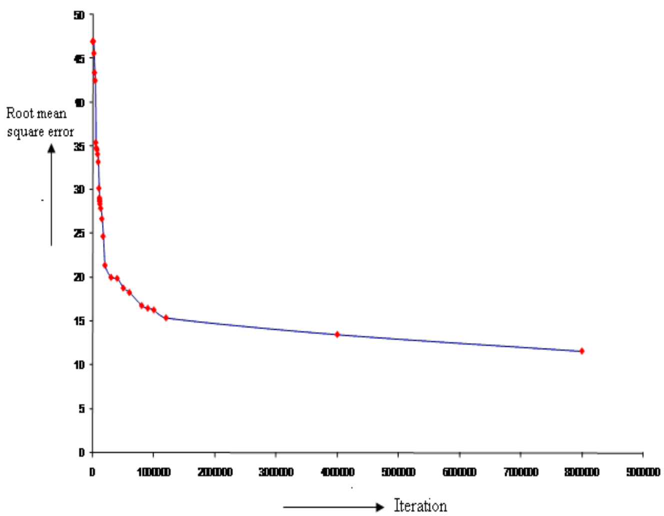

Figure 7 Cumulative error Vs iteration of tested Neural Network

was trained with 335 data sets and a weight matrix yielding satisfactory output was obtained. AANN was tested and the output shown in Table 2 was obtained. It can be observed that the drift in stator current due to various faults in all the three phases is compensated by the neural network validating that trained neural network restores back the closest possible original value of stator current achieving the sensor drift compensation of the Induction motor..

Table 2 Stator current output with and without Neural Network compensation

S.No.	Actual Stator current	Stator current with error without compensation	Stator current with NN compensation
1)	17	1.5	16.8963
2)	17	13	17.1034
3)	18	1.7	17.9420
4)	18	10	17.6813
5)	19	11	19.5653
6)	19	7	19.0772
7)	20	15	20.1489
8)	20	6.5	19.8912
9)	21	6	20.8756
10)	21	3	21.7502
11)	22	2.1	22.5011
12)	22	12	21.9784
13)	23	14	22.4884
14)	23	20	22.0867
15)	23	16	22.3678

Table 2 indicates that the trained neural network eliminates the error ands restores the nearest possible original value of stator current.

7. CONCLUSION

Vector controlled Induction motor drive system has been tested with uncompensated and compensated sensor outputs to validate the performance using Auto associative neural network adopting supervised learning algorithm. The neural network has been trained with 335 sets of input data (1005) and tested to obtain a satisfactory output. The cumulative root mean square error between the faulty stator current and the neural network compensated stator current was found to be 11.93. This concludes that the trained neural network compensates for the drift in various stator current occurring due to various faults and restores back the closest possible original value of stator current. Further this can be extended by reducing the cumulative root mean square error by choosing a different algorithm or fixed weight network. By implementing the above said networks, performance of neural network for sensor drift compensation can be further improved.

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