

Parameter Estimation for Performance Enhancement of Indirect Field Oriented Induction Motor Drives: A Survey

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Abstract: The advent of fast computing digital processors has made vector controlled induction motor drives realisable and its applications have increased manifold. For performance enhancement, it is essential to accurately estimate the parameters of the induction motor. On line estimation of parameters continue to be challenging. This study presents a review of the developments in the field during the last two decades. A large number of research studies have been published during the above period, proposing different techniques for estimation of rotor and stator resistances. Among the two, the rotor resistance is more sensitive to temperature rise and ageing and therefore has a critical impact on detuning of the control algorithm. Hence in comparison, only limited researches have dealt with stator resistance estimation. This review covers the well accepted methods of parameter estimation namely spectral analysis, observer based techniques, model reference adaptive system and intelligent techniques. Attempt is made to provide a precise and quick reference for the researchers and practising engineers working in the area of vector control.

Key words: Scalar based control, vector control, rotor resistance, stator resistance spectral analysis, observer based, Model Reference Adaptive System (MRAS), intelligent methods

INTRODUCTION

During the past three decades, adjustable speed ac drive technology has gained a lot of momentum. The variable speed drive scenario is characterized by the cage induction motor, wound rotor synchronous motor and the new category of permanent magnet brushless synchronous and dc motors. The induction motor is very popular in drive applications due to its well known advantages of simple construction, ruggedness and less cost. Progress in the field of power electronics has enabled the application of induction motors for variable speed high-performance drives where traditionally, only dc motors were preferred (Blaschke, 1972). Earlier, induction motors were controlled using scalar control methods like the voltage-hertz control.

A major revolution in the area of induction motor based drives was the invention of field oriented or vector control in the late 1960's (Blaschke, 1972). The scenario of variable speed control of cage induction motor is shown in Fig. 1. It is basically classified into 2 types: scalar based control and vector based control. In scalar control, only the magnitude and frequency of voltage, current and flux linkage variables are controlled. This scheme can control the speed of the motor satisfactorily under steady-state only.

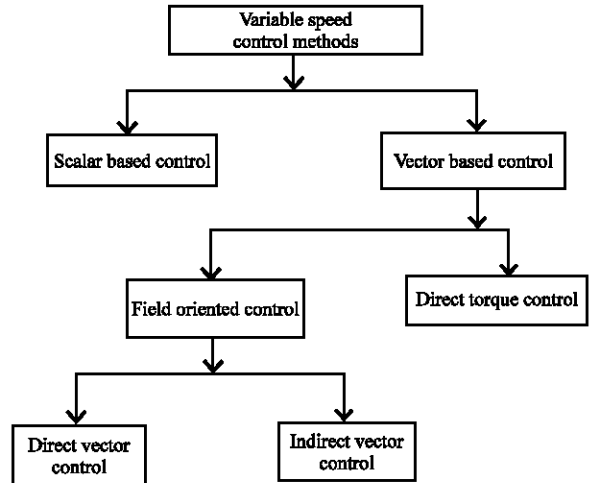


Fig. 1: Overview of induction motor control

In vector control, the magnitude, frequency and instantaneous orientation of voltage, current and flux linkage vectors are controlled and is valid for steady-state as well as transient conditions. Thus, the vector control method is superior to scalar control when dynamic performance is important. With the advent of vector control schemes, the control of an induction motor is transformed similar to the control of a separately excited

dc motor by creating independent channels for flux and torque control. Assuming that the rotor flux orientation is known, the stator current phasor is resolved along and in quadrature to it. The in-phase component is the flux generating component, i_f and the quadrature component is the torque component, i_T . The resolution of the current requires the knowledge of the rotor flux orientation which is known as field angle, θ_f . This field angle can either be measured or estimated (Bose, 2003).

Using measured field angle in the control scheme is known as direct field control and that using estimated field angle is known as indirect vector control scheme. The absence of field angle sensors and the ease of operation at low speeds compared to the direct vector control scheme has increased the popularity of the indirect vector control strategy. Indirect vector control of an induction motor presents good tracking for flux and immediate tracking for torque. Since, successful implementation of indirect field oriented control requires an accurate calculation of field angle and slip frequency, a d-q axis mathematical model of the machine along with parameter values is needed.

However, the errors in the model parameters can cause incorrect coupling between flux and torque; the result is a mismatch between the torque command and the motor torque in the steady-state mode on the one hand and an oscillatory response of the transient torque on the other. Detuning of the rotor parameters renders implementation of an indirect rotor flux oriented control scheme unsatisfactory and dependent on operational conditions of the motor such as temperature, frequency and the saturation level of the machine.

High performance control requires an accurate estimate of the machine parameters at all operating points; it should be done continuously on-line. Various schemes have been proposed for rotor time constant adaptation such as the model reference adaptive control technique, an extended kalman filter and spectral analysis method. Artificial neural network methods for the estimation of rotor time constant were also investigated (Vas, 1990).

In indirect field oriented control, the major problem is the rotor resistance which is sensitive to temperature. The practical temperature excursion of the rotor is approximately 130°C above ambient temperature (Krishnan and Doran, 1987). This increases the rotor resistance by 50% over its ambient or nominal value. When this parameter is incorrect in the control algorithm, the calculated slip frequency is incorrect and the flux angle is no longer appropriate for field orientation.

This results in instantaneous error in both flux and torque which can be shown to excite a second order transient characterized by an oscillation frequency equal

to the command slip frequency. The R_r estimation algorithm requires the knowledge of stator resistance R_s that may also vary up to 50% during motor operation. Hence, the error in the values of R_s leads to errors in R_r estimation also. The problem is overcome by adding another on-line estimation for R_s to the system, providing total immunity from both stator and rotor resistance variations.

For combining stator and rotor resistance estimation, problems relating to simultaneous variation of multiple parameters has to be understood. Here, one approach is for on-line rotor resistance estimation, the stator resistance is assumed constant and for on-line stator resistance estimation, the rotor resistance is assumed to be constant. So for combining both the estimators, one estimator will be inactive initially and after the estimation, the parameter is passed to the other estimator.

MATERIALS AND METHODS

Rotor resistance estimation methods: The on-line methods of rotor resistance identification developed so far could be broadly classified under the following categories:

- Spectral analysis techniques
- Observer based techniques
- Model reference adaptive system based techniques
- Intelligent techniques

Spectral analysis techniques: The spectral analysis techniques are based on the measured response to a purposely injected test signal on an existing characteristic harmonic in the voltage/current spectrum. Stator currents and/or voltages of the motor are sampled and the parameters are derived from the spectral analysis of these combined samples. In the case of spectral analysis, a perturbation signal is used because under no load conditions of the induction motor, the rotor induced currents and voltages become low leading to small values of slip frequency and rotor voltages. Hence, the rotor parameters cannot be estimated using this method. This class of parameter estimation technique involving signal injection is proposed by Nomura *et al.* (1987) and Wade *et al.* (1997). It is an on-line method which does not require voltage sensors; computation is simpler and superior to extended kalman filter and the extended luenberger observer.

Matsuo and Lipo (1985) and Toliyat and Hosseiny (1993) have proposed injecting negative sequence components as the disturbance to the system. The former publication deals with an on-line technique for

determining the value of rotor resistance by detecting the negative sequence currents at 2 different frequencies so that the rotor resistance can be uniquely derived.

Toliyat and Hosseiny (1993) presented another on-line estimation technique by using the d-q model in the frequency domain. By keeping the q-axis component of the motor flux unchanged the disturbance is confined to the d-axis component. By employing FFT of the currents and voltages, the fundamental components of the sampled spectral values are obtained for the parameters estimation. Gabriel and Leonard (1982) proposed a correlation method to detect misalignment between the actual motor flux and the rotor flux given by the model.

A small auxiliary signal is added to the d-axis flux component of the stator current and a correlation function is evaluated. The nonzero value of the correlation function indicates both coupling between fluxes and discrepancies between the parameters of the model and those of the motor.

Gao *et al.* (2008) proposed a sensor less rotor temperature estimator for small to medium sized mains fed induction machines. With measurements obtained only from voltage and current sensors, the proposed estimator can capture the rotor temperature online. The rotor speed is first extracted from the stator current harmonic spectrum based on the estimated rotor slot and eccentricity harmonic frequencies.

Then the inductances are estimated according to the induction machine equivalent circuit. The stator winding resistance at ambient temperature is the only motor parameter needed as input at this stage. Once the inductances are obtained, they are fed into the rotor resistance estimation algorithm to yield an estimate of the rotor resistance.

In this method, the rotor resistance can be obtained from the spectral analysis of the stator current or stator voltage measurements. The main drawbacks of this method are the adverse effect of injecting signal on motor dynamics and the requirement of extra hardware for signal injection.

Observer based techniques: The second classification of rotor resistance identification methods can be grouped under observer based techniques. This class of parameter identification technique is based on either Extended Kalman Filter (EKF) or Extended Luenberger Observer (ELO) or adaptive observer. Here, the rotor time constant is treated as additional state variable along with rotor speed so that the above methods can be used for joint state and parameter estimation efficiently. The researchers have applied extended observer techniques for state and parameter estimation for high performance ac

drives. However, the problems related to Extended Kalman Filter (EKF), Extended Luenberger Observer (ELO) are the large memory requirement, computational intricacy and the constraint such as treating all inductances to be constant in the machine model.

Finch *et al.* (1998) proposed an application of EKF for tuning an IFO drive. Here, the Riccati difference equation is replaced by a lookup table. Although, the complexity of Riccati equation is reduced, the full-order EKF is computationally very intensive. In this study, the application of the full extended kalman filter algorithm to the online estimation of rotor resistance required for the slip calculation algorithm of indirect vector control is presented. Temperature variations in rotor resistance can be tracked as they occur by making use of a Riccati equation.

Markadeh *et al.* (2005) proposed a new adaptive rotor flux observer for speed sensor less induction motor drives which provides the rotor speed, stator and rotor resistances estimations simultaneously. The rotor speed and rotor flux controllers are designed based on combination of input-output feedback linearizing, sliding mode control and Linear quadratic feedback control. It was shown that the composite rotor speed and rotor flux controllers in combination with adaptive flux observer guarantee the system stability and robustness against the parameter variations and external load disturbance under persistency of excitation condition. The persistency of excitation condition is satisfied if a low frequency ac signal is superimposed to the rotor reference flux under motor load operation.

Aloliwi *et al.* (1999) proposed a nonlinear robust adaptive output feedback speed controller for induction motors. The control uses only measurements of the rotor position, stator current and temperature. It contains two observers, a 9th order adaptive observer to estimate the rotor flux and rotor resistance and a 3rd order high gain observer to estimate the rotor speed and acceleration from its position. The control is robust to uncertainties in the motor parameters and a bounded time varying load torque.

Model reference adaptive system based techniques: The 3rd group of on-line rotor resistance adaptation methods is based on principles of model reference adaptive control. This is the approach that has attracted most of the attention due to its relatively simple implementation requirements. Here, the basic idea is to estimate certain states from two different directions, one is to calculate using the states of the controllers and the other is to estimate the same states using measured signals. One of the estimates should be independent of rotor resistance,

so that the error between these 2 estimates provide the correction to the rotor resistance using an adaptive mechanism which can be a proportional controller. These methods essentially utilize the machine model and its accuracy is therefore, heavily dependent on the accuracy of the model used. In general, these methods primarily differ with respect to which quantity is selected for adaptation purposes.

Some of the best known are electromagnetic torque based, rotor flux based, outer product of stator current and back emf based, reactive power based, air gap power based, stator fundamental rms voltage based and d-axis and q-axis stator voltage based. One of the common features that all of the methods of this group share is that rotor resistance adaptation is usually operational in steady-states only and is disabled during transients.

Torque reference model: Lorenz (1990) proposed a simplified approach to the continuous on-line tuning of rotor flux feed forward field oriented induction motor drive. This procedure offers the advantages of not requiring a special test signal or special test conditions. The approach takes advantage of the stator voltage equations which allow robust and parameter insensitive estimation of the electro-magnetic torque while operating at nominal speeds for which the stator IR voltage drop is negligible.

It uses the torque equation to estimate the rotor resistance. This estimation can be used even under transient torque conditions. However, there is a need to know the values of stator resistance (also variable with temperature), the magnetising inductance and the rotor inductance.

The reactive-power reference model: Garces proposed a method in which reactive-power equation used to estimate the rotor resistance. This method uses stator inductance, rotor inductance and magnetising inductance but there is no need to know the stator resistance. A thorough analysis of the convergence of the rotor resistance estimate to its actual value shows a strong dependency on the operating point (supply frequency and load torque).

Maiti *et al.* (2008) proposed a detailed study on the Model Reference Adaptive Controller (MRAC) utilizing the reactive power for the online estimation of rotor resistance so as to maintain proper flux orientation in an indirect vector controlled induction motor drive. Selection of reactive power as the functional candidate in the MRAC automatically makes the system immune to the variation of stator resistance. Moreover, the unique formulation of the MRAC with the instantaneous and

steady-state reactive power completely eliminates the requirement of any flux estimation in the computation process.

Thus, the method is less sensitive to integrator related problems like drift and saturation and also makes the estimation at or near zero speed quite accurate.

Rotor flux based model: Karanayil *et al.* (2007) proposed a new method of online estimation for the rotor resistance of the induction motor for speed sensorless indirect vector controlled drives using artificial neural networks. The error between the rotor flux linkages based on a neural network model and a voltage model is back propagated to adjust the weights of the neural network model for the rotor resistance estimation.

Outer product of stator current and back EMF method: To solve the problem of performance degradation due to parameter variations in an indirect vector control of an induction motor, a novel and simple estimation method for rotor circuit time constant was presented by Tungpimolrut *et al.* (1994). The proposed method is based on regulating the energy stored in the magnetizing inductance which can be calculated from the terminal voltages and magnetising currents.

The d-axis and q-axis voltage reference models: In Rowan *et al.* (1989), the d-axis and the q-axis voltage equations are used to estimate the rotor resistance. Both approaches use stator resistance, stator and rotor inductances and magnetising inductance. The error between the estimated voltage and the real value is analysed.

This error is used to drive adaptive mechanism which provides estimation of the rotor resistance, it is demonstrated that the load torque and the supply frequency affect the convergence of the algorithm in this case. The MRAC methods are strongly dependent on the accuracy of the machine model and estimation is usually based on the steady-state machine model.

Further in most cases, the adaptation process does not work at zero rotor speed and at zero load torque. Some methods based on MRAC take changes in the magnetising inductance and the operation at light load torques into account (Vukosavic and Stojic, 1993).

Intelligent techniques: Recent developments in artificial intelligence have led to the application of artificial neural networks and fuzzy logic for the on-line rotor time constant/rotor resistance adaptation. Bim proposed a fuzzy rotor time constant identification based on a fuzzy optimisation problem in which the objective function is

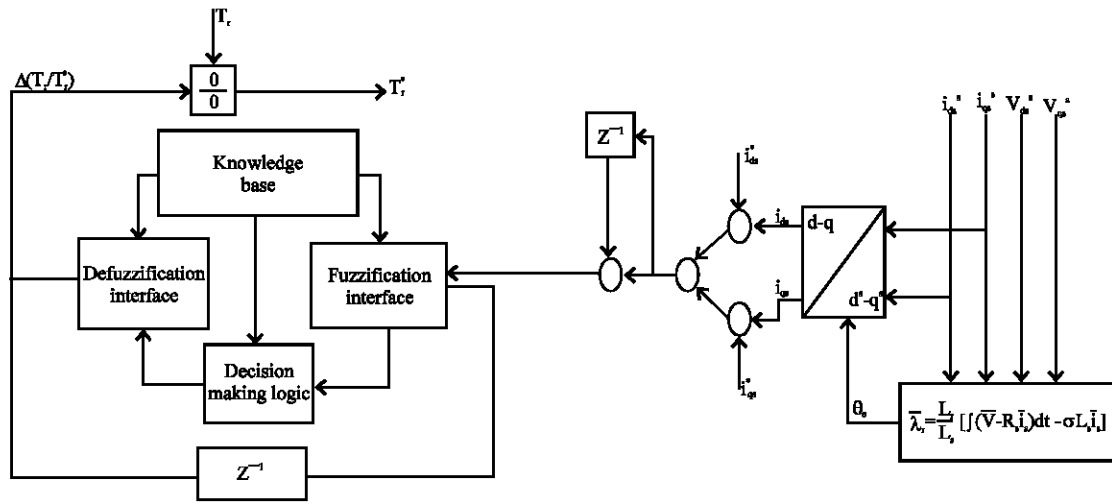


Fig. 2: Fuzzy logic based T_r updating scheme for indirect FOC proposed by Bim (2001)

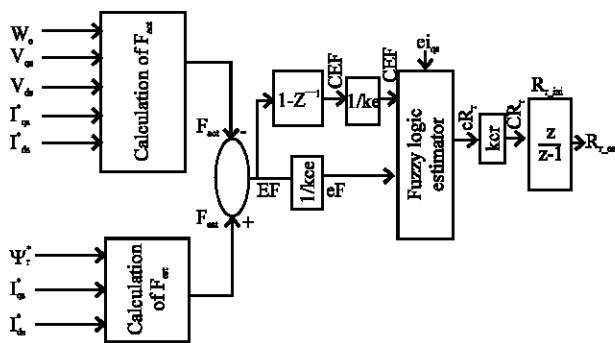


Fig. 3: Rotor resistance estimator using fuzzy logic proposed by Ta-Cao and Le-Huy (1998)

the total square error between the commanded stator currents and measured stator currents in the d-q reference frame as shown in Fig. 2. Because the variation of the motor thermal time constant is very slow compared with the motor electrical time constant, a sampling interval of 5 sec was chosen.

Ta-Cao and Le-Huy (1998) estimated the rotor resistance with only the steady-state measurements assuming the resistance variation is very slow. Their estimation was based on a characteristic function F defined by:

$$F = \frac{1}{\omega_e} \left[i_{qs} \frac{d\lambda_{dr}}{dt} - i_{ds} \frac{d\lambda_{qr}}{dt} \right]$$

This characteristic function was estimated using the reference values as F_{est} and was calculated from the measured voltages and currents as F_{act} . The error between

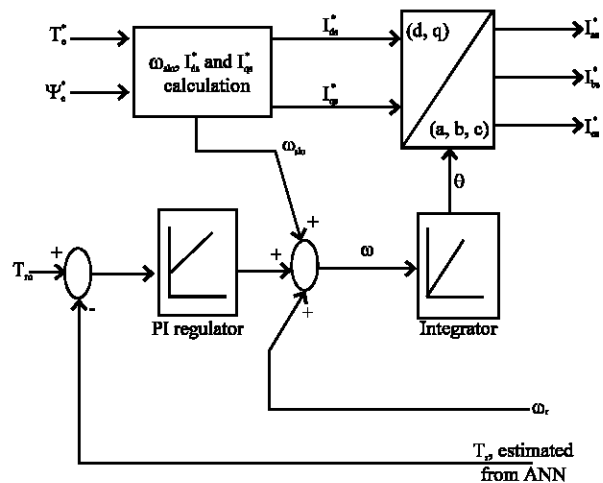


Fig. 4: Principle of rotor time constant adaptation proposed by Ba-Razzouk *et al.* (1996)

the estimated and actual value of characteristic function is used to estimate the rotor resistance variation is shown in Fig. 3. Ba-Razzouk *et al.* (1996) proposed another ANN method for rotor time constant adaptation in IFO controlled drives. There are 5 inputs to the T_r estimator using neural network, namely V_{ds}^s , V_{qs}^s , i_{ds}^s , i_{qs}^s , ω_r . The training signals are generated with step variations in rotor resistance for different torque reference T_r^* and flux command and the final network is connected in the IFO controller as shown in Fig. 4. The rotor time constant was tracked by a PI regulator that corrects any errors in the slip calculator.

The output of this regulator is summed with that of the slip calculator and the result constitutes the new slip command that is required to compensate for the rotor time

constant variation. The major drawback of this scheme is that the final neural network is only an off-line trained network with a limited data file in the modelling. Mayaleh and Bayinder (1998) proposed a rotor time constant estimation using a recurrent neural network, their algorithm used the 3 stator voltage and 3 stator current measurements in the stator reference frame. The rotor time constant was obtained at the output of a Recurrent Neural Network (RNN) as shown in Fig. 5. The 3 inputs to the RNN were stator currents, rotor fluxes and rotor speed.

Here, the rotor flux was calculated using motor parameters and the influence of stator resistance on rotor flux estimation was not accounted for. Even though, the results and the method employed were elegant, these results were not backed up by experimental data subsequently. The back propagation algorithm is used for training of the neural networks (Karanayil *et al.*, 2007) shown in Fig. 6. The error between the rotor flux linkages

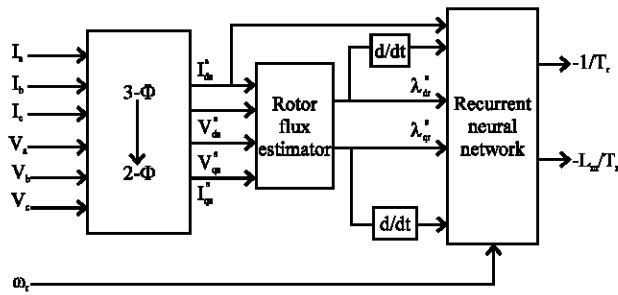


Fig. 5: Rotor time constant estimator proposed by Mayaleh and Bayinder (1998)

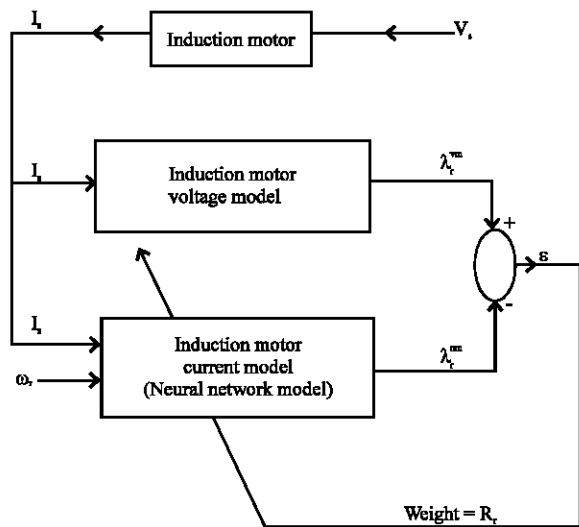


Fig. 6: Structure of the neural network system for R_r estimator proposed by Karanayil *et al.* (2007)

based on a neural network model and a voltage model is back propagated to adjust the weights of the neural network model for the rotor resistance estimation. With this approach, the rotor resistance estimation was found to be insensitive to the stator resistance variations both in simulation and experiment. Ebrahimi *et al.* (2006) proposed a scheme for the estimation of rotor resistance using a Neural Networks (NN) block as shown in Fig. 7. In this system, the flux and torque have been estimated by using stator voltages and currents.

A back propagation NN receives the flux and torque errors and a supposed rotor resistance at the input and estimates the actual rotor resistance at the output which is used in the control of indirect vector controlled drive system.

The neural network has been trained off-line with the mathematical model of the control scheme. Indirect rotor flux oriented control used with the NN estimator has been studied in the detuning condition. The performance of the controller was good even when the rotor time constant was increased from nominal value to twice the nominal value as well as torque variations. In this method, estimation was done quickly and accurately and its design was simple.

Other methods: Chan and Wang (1990) have presented a new method for rotor resistance identification with a new coordinate axes selection. They set a new reference frame which was coincident with the stator current vector. The simulation involves the steady-state motor model and 3-2 phase transformation. Using the simulation results of stator voltage, current and speed in the steady-state, the stationary reference frame components were obtained using which the rotor resistance is calculated algebraically during simulation. Toliyat *et al.* (1999) proposed a rotor time constant updating scheme which neither required any special test signal nor any complex computation. This

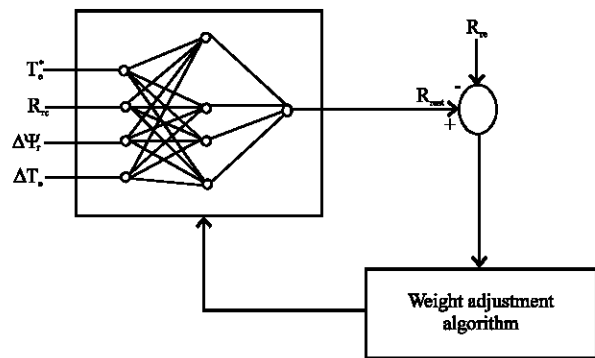


Fig. 7: Procedure of training neural network proposed by Ebrahimi *et al.* (2006)

technique utilized a modified switching technique for the current regulated pulse width modulation voltage source inverter to measure the induced voltage across the stator terminals. The induced voltage was measured at every zero crossing of the phase currents. Thus for the 3 phase induction motor, the proposed technique provided 6 instants to update the rotor time constant. The technique was capable of measuring the rotor time constant for the minimum stator frequency of 5 Hz.

Stator resistance estimation methods: Marino *et al.* (2000) addressed the problem of simultaneous on-line estimation of both rotor and stator resistances based on the measurements of rotor speed, stator currents and stator voltages. Their main contribution was in designing a novel 9th order estimation algorithm which contains both rotor flux and stator current estimates. Their design goal was to force stator current estimation errors to tend asymptotically to zero for any initial condition. They have shown in this study that both stator and rotor resistance estimates converged exponentially to the true values for any initial value of stator and rotor resistances.

Bose and Patel (1998) described a quasi-fuzzy method of on-line stator resistance estimation of an induction motor where the resistance value is derived from stator winding temperature estimation as a function of stator current and frequency through an approximate dynamic model of the machine.

The dynamic thermal model of the machine can be approximately represented by a first order low pass filter as shown in Fig. 8. Once, the steady-state temperature is estimated by the fuzzy estimator block, it is then converted to dynamic temperature rise through the low pass filter and added to ambient temperature T_A to derive the actual stator temperature T_{st} . Neglecting the small

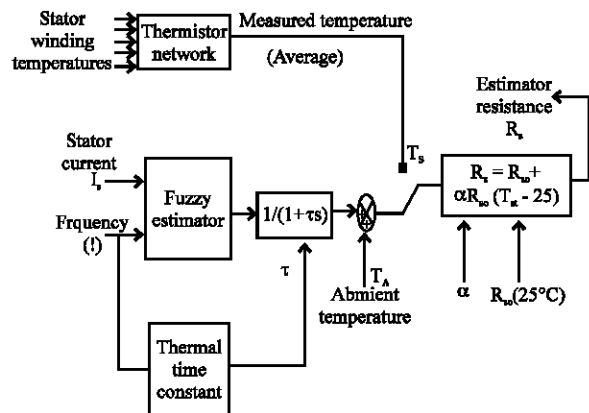


Fig. 8: Quasi-fuzzy stator resistance estimator block diagram proposed by Bose and Patel (1998)

amount of skin and stray loss effects, the stator resistance R_s is then estimated from the measured temperature rise of the stator winding using the equation shown in Fig. 8.

Guidi and Umida (2000) proposed an observer based method for online estimation of the stator resistance of an induction machine and a speed sensorless field oriented drive equipped with the proposed estimator was built. The drive is particularly suitable for low-speed operation. Resistance is based on a two-time scale approach and the error between measured and observed current is used for parameter tuning. The simple full order observer in use allows for direct field orientation in a wide range of operation. Holtz and Quan (2002) proposed a scheme to overcome problems related to parameter estimation at low stator voltage and low speed operation. A pure integrator was used for stator flux estimation which permits high estimation bandwidth. Increased accuracy was achieved by eliminating direct stator voltage measurement instead the reference voltage corrected by a self adjusting non linear inverter model was used. The time varying disturbances were compensated by an estimated offset voltage vector. The stator resistance estimation algorithm relies on the orthogonal relationship between the stator flux vector and the induced voltage in the steady-state. The stator resistance was found from the inner product of these 2 vectors in current coordinates. Current coordinates is a reference frame aligned with the current vector. The signal flow graph of this stator resistance estimation scheme is shown in Fig. 9.

Ha and Lee (2000) proposed an identification algorithm for stator resistance which has been based on the steady-state power flow between stator and rotor through the air gap. The steady-state power across the air gap was represented as the difference between the steady-state input power and the steady-state power

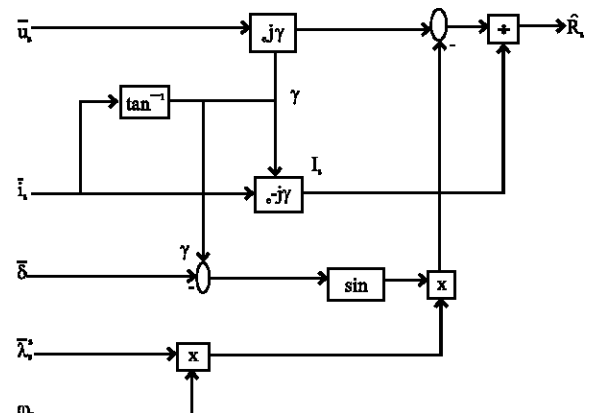


Fig. 9: Signal flow graph of the stator resistance estimate or proposed by Holtz and Quan (2002)

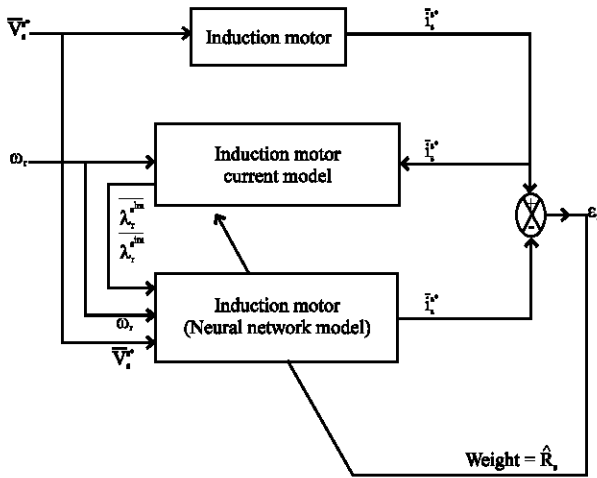


Fig. 10: Stator resistance estimation using artificial neural network proposed by Karanayil *et al.* (2007)

dissipated by the stator windings. The air gap power was calculated using the steady-state value of estimated torque. The stator resistance was then estimated using the difference between these 2 steady-state powers. They have reported that the identification algorithm should be executed only in the steady-state and cannot do estimations during transient conditions.

Karanayil *et al.* (2007) proposed a new method of online estimation for the stator and rotor resistances of the induction motor for speed sensorless indirect vector controlled drives using artificial neural networks. The error between the flux linkages based on a neural network model and a voltage model is back propagated to adjust the weights of the neural network model for the rotor resistance estimation as shown in Fig. 10.

For the stator resistance estimation, the error between the measured stator current and the estimated stator current using neural network is back propagated to adjust the weights of the neural network. The rotor speed is synthesized from the induction motor state equations. The performance of the stator and rotor resistance estimators, torque and flux responses of the drive together with these estimators are investigated with the help of the simulations for variations in the stator and rotor resistances from their nominal values. Additionally, the researcher has done both resistances estimation experimentally using the proposed neural network in a vector controlled induction motor drive.

CONCLUSION

The detailed study of rotor resistance and stator resistance estimation methods of an induction motor is reported. This review study has covered the well

accepted methods like spectral analysis, observer based techniques, model reference adaptive system etc., which are mainly related to rotor resistance estimation. The literature on application of ANN and fuzzy techniques used for estimation in induction motor drives has been reviewed. These techniques have also found applications in controllers of indirect field oriented drives. The studies on the development of ANN and other estimators initially assumed the availability of an accurate speed sensor. Estimation techniques for sensorless operation of vector control drives has now become an important research goal.

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