ISSN 2347 - 3983

**International Journal of Emerging Trends in Engineering Research (IJETER), Vol. 3 No.6, Pages : 442 - 447 (2015)**
*Special Issue of NCTET 2K15 - Held on June 13, 2015 in SV College of Engineering, Tirupati*
***http://warse.org/IJETER/static/pdf/Issue/NCTET2015sp79.pdf***

# A Review Online Estimation of Rotor Resistance for Vector Controlled Induction Motor Drive

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**ABSTRACT**

Identification of Rotor parameters plays a major role in vector controlled induction motor drives. Among those parameters rotor resistance identification has been well recognized as one of the most critical factors affecting the theoretical study and applications of AC motor's control for high performance variable frequency speed tuning. This paper presented in this article can support the state of some related researches. It summarizes many previous works on online identification of rotor resistance. Finally estimation of rotor resistance of vector controlled IM drive by using Artificial Neural Network has been presented. The trained back propagation network, applied in the identification model, is able to efficiently predict the rotor resistance in high accuracy. The simulation and experimental results show that the proposed method owns extensive adaptability and performs. Very well in its application to vector controlled induction motor

**Key words:** Induction motor, scalar control, vector control, voltage model, current model, Artificial Neural Network, Back propagation

## 1. INTRODUCTION

Induction machines have several advantages over DC machines such as low cost, robustness, high reliability. Although traditionally DC machines have been used for high performance adjustable speed applications. From last two decades development power electronics have been increased sharply. This development in power electronics has contributed to the use of advanced control techniques that have made it possible to extend to use of induction machines in those applications. Basically there are two types of control techniques in induction motor. One is scalar control another one is vector control.

Scalar control as the name indicates is due to the magnitude variation of control variables only and disregards the coupling effects in the machine. Scalar control drives gives somewhat inferior performance, but they are easy to implement. Scalar control drives have been widely used in industry. However its importance has reduced recently because of the superior performance of the vector controlled drives which is demanded in many applications.

The vector control allows not only control of the voltage amplitude and frequency, like in the scalar control methods, but also the instantaneous position of the voltage, current and flux vectors. This improves significantly the dynamic behavior of the induction motor. However, induction motor has a nonlinear behavior and there exist a coupling in the motor, between flux and the produced electromagnetic torque. Therefore, several methods have been proposed for decoupling torque and flux. These algorithms are based on different ideas and analysis the first vector control method of induction motor was *Field Oriented Control* (FOC) presented by K. Hasse (Indirect FOC) [1] and F. Blaschke (Direct FOC) [2] in early of 70s.

Vector control is becoming a standard tool for industrial motor drives. There are two different approaches in the area of vector control: the direct vector control in which the rotor flux position and amplitude are estimated, and the indirect vector control in which only the rotor flux position is used [2,3] . The indirect rotor flux oriented control method (IRFOC) offers the most interesting characteristics and is thus widely used in high performance drives. The main features of the IRFOC are the simplicity of its implementation and the linearity of its steady state torque-slip characteristics. So it constitutes a judicious and attractive choice for a generalized implementation of high performance adjustable speed ac drives using induction motors.

In vector control for induction motor the key point lies in the magnetic field orientation, but one of the important factors affecting the field orientation is the accuracy of rotor parameters. While an AC motor is running, motor parameters may change with the influence of inner and outer conditions. The changes of the slip frequency and motor temperature can affect rotor resistance value. This will change the rotor time constant value. The decoupling conditions of the torque and flux control are destroyed when the rotor time constant deviates from actual value largely. In order to improve the performance of induction motor vector control System, it is

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necessary to initiate the online identification of motor parameters.

Mainly there are three categories on the online parameter identification: spectrum analysis technology, the observer- based technology, and the model reference adaptive identification technology.

In spectral analysis methods are based on the measured response to a specific injected signal or a characteristic harmonic in the voltage or current spectrum. By the spectral analysis of the stator current or voltage measurements we can obtain the required parameters. As mentioned in [5], based on *d-q* model in frequency domain, the *q* axis component into the negative sequence signal remains zero, so that the motor torque is not disturbed. The fast Fourier transform is used to analyze the fundamental component of current and voltage as well as the samples spectral values, and the results were used to determine the parameters of the motor.

Several proposed methods using extended Kalman filters or extended Luenberger observers have been developed to estimate the rotor resistance in induction machines in this technology, the motor's parameters are processed as the system extended state. With the condition of the induction motor normal operating, the extended motor model and the EKF method on the motor parameter estimation are described in [6]. This method requires the motor ending signal and rotor speed measurement. Reference [7] adopts the wideband harmonic contained in the PWM inverter output voltage to estimate the rotor time constant with EKF algorithm. The extended Luenberger observer for estimating the critical state and parameters in the motor is explained in [8–10]. The main problem of EKF and ELO is the strength of the calculation. The more the numbers of parameters estimation of the expansion are, the more the strength calculation increases rapidly. The main drawbacks of these methods are computational cost and the fact that the inductances are considered constant.

The characteristics of the model reference adaptive identification technique are simple, but its accuracy depends on the accuracy of the system model. The method depends on other parameters of the sensitivity, it is better to guesstimate some other parameters during the adaptive adjustment. When the order of the magnetizing inductance variation with the degree of saturation of the motor is considered, the identification accuracy of the stator and the rotor resistance are further enhanced [11–16]. Additionally, online identification of rotor resistance for vector controlled induction motor has been focused on more and more. A time-varying parameter identification algorithm is presented in [17], which is simple and easy for online estimation of the rotor resistance for induction motor with the rapidly convergence in spite of measurement disturbances (like noise, discretization effects, parameter uncertainties, and modeling inaccuracies). But the acquisition of reference model always has difficulties.

Model reference adaptive control techniques have been used frequently to estimate the rotor resistance due to their simple implementation. Some of the best known are The Torque Reference Model uses the torque equation to estimate the rotor resistance [18].This estimation can be used even under transient torque conditions. However, there is a necessitate to know the stator resistance (also variable with temperature), the magnetizing inductance and the rotor inductance. Although the implementation of this method is analyzed and the convergence is not studied in detail.

The Reactive-Power Reference Model uses the reactive-power equation to estimate the rotor resistance [19]. This method uses the motor parameters like stator inductance, rotor inductance and magnetizing inductance, but there is no need to know the stator resistance. A systematic analysis of the convergence of the resistance estimate to its actual value shows a strong dependency on the operating point (supply frequency and load torque). This issue needs further investigation and is one of the contributions of this paper.

(a)The D-Axis and Q-Axis Voltage Reference Models

Use the d-axis voltage equation and the q-axis voltage equation, respectively, to estimate the rotor resistance. Both approaches use stator resistance, magnetizing inductance, stator and rotor inductances. The error between the estimated voltage and the actual value is analyzed in steady state in [20]. This error is used to drive the adaptive mechanism which provides estimation of the rotor resistance. It is demonstrated that the load torque and the frequency of the also affect the algorithm convergence 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. Furthermore, in most cases, the adaptation process does not work at zero rotor speed and at zero load torque.

In recent years, new algorithms to estimate rotor resistance have been developed using non linear control theory, power electronic technology developed and the wide use of DSP's control of induction Machine.

## 2. DYNAMIC MODELLING OF INDIRECT ROTOR FLUX ORIENTED CONTROL OF IM

At first, the mathematics model in the 2-phase synchronous rotating coordinate system of the induction motor is presented. The 2-phase synchronous rotating coordinate system is a special case of two arbitrary rotation coordinates rotating in synchronous speed. Mathematical model equations with this system of the induction motor are

ISSN 2347 - 3983

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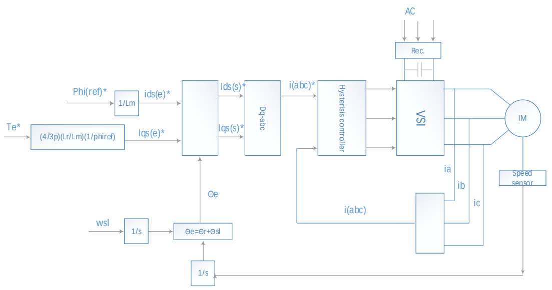

**Fig.1.Block diagram of indirect vector control of an IM**

Following equations are valid for rotating frame $d^e - q^e$ equivalent circuits

$$\frac{d\varphi_{qr}^e}{dt} + \frac{R_r}{L_r}\varphi_{qr}^e - \frac{L_m}{L_r}R_r i_{qs}^e + w_{sl}\varphi_{dr}^e = 0 \qquad (1)$$

$$\frac{d\varphi_{dr}^e}{dt} + \frac{R_r}{L_r}\varphi_{dr}^e - \frac{L_m}{L_r}R_r i_{ds}^e + w_{sl}\varphi_{qr}^e = 0 \qquad (2)$$

For decoupling control it is desirable that

$$\varphi_{qr}^e = \frac{d\varphi_{qr}^e}{dt} = 0$$

$$\varphi_{dr}^e = \varphi_r = constant$$

$$\frac{d\varphi_{dr}^e}{dt} = 0$$

Substituting the first two conditions, Eqn (1) and (2) can be simplified as

$$w_{sl} = \frac{L_m}{\varphi_r}\left(\frac{R_r}{L_r}\right)i_{qs}^e$$

## 3. ESTIMATION OF ROTOR RESISTANCE BY ANN

Artificial neural network is increasingly used for parameter identification in recent times. It is demonstrated systematically that the neural networks are applied to electrical drive systems in [18] and give valuable instruction of their online and offline. These studies proved neural network's applicability to motor parameter identification theoretically and practically.

The model of rotor resistance identification based on back propagation neural network is proposed in this paper. It was invented independently several times Bryson an Ho [1969] , Werbos [1974], Parker [1985], Rumelhart et al. [1986]

It is a popular learning method and capable of handling large learning problems. It has been one of the most studied and used algorithms for neural networks learning ever since. The algorithm gives an instruction for changing the weights Wij in any feed forward network to learn a training set of input output pairs {xd, td}.

In this paper, a new type of induction motor rotor resistance estimator based on the artificial neural network technology has been presented. It can adjust the weights of neural network through the flux error between neural network model and a typical motor model to achieve the purpose of identification of rotor resistance parameters.

### 3.1. **Principle and structure of observer**

Fig.1. describes the basic structure of a rotor resistance estimation model. There are two modules in the model. One is rotor flux linkages estimation module; here rotor flux is estimated from the input voltages and currents of induction machine. The other is rotor flux linkages current ANN module, here the flux linkages are obtained from input currents and speed of the machine. Two independent modules are used to estimate the rotor flux vector of the induction motor. The flux linkage error between two modules inputs into MLPANN. Back propagation algorithm can adjust weights. At last, the output of the later tail after the output of former. At this time, the progress of training is fulfilled. The weight of MLPANN relate to the parameter of motor. The identical of real and estimate rotor resistance can be achieved by the indirect method.

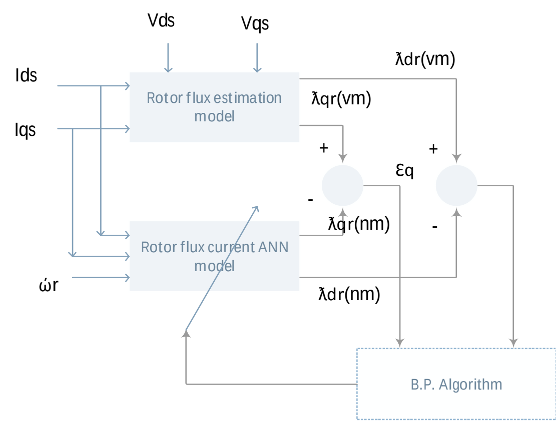


Fig. 1.Estimation of rotor flux linkages from voltage model

In the proposed system, the outputs of the neural networks are fluxes (i.e. d-axis & q-axis fluxes). These fluxes are compared with fluxes from the voltage model. So these fluxes must be estimated. It is possible to establish a flux which does not use the monitored speed, but uses only the monitored values of stator voltages and currents. This model does not depend on rotor resistance. So the estimated flux is accurate and correct, even if the rotor resistance has some variation due to temperature variation and skin effect.

The following equations of stator voltages and fluxes can be written from stationary frame equivalent circuits.

$$v_{qs}^s = R_s i_{qs}^s + \frac{d\varphi_{qs}^s}{dt}$$

$$v_{ds}^s = R_s i_{ds}^s + \frac{d\varphi_{ds}^s}{dt}$$

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$$\varphi_{qs}^{s} = L_s i_{qs}^{s} + L_m i_{qr}^{s}$$
$$\varphi_{ds}^{s} = L_s i_{ds}^{s} + L_m i_{dr}^{s}$$

The rotor currents can be derived from stator voltages and currents as:

$$i_{qr}^{s} = \frac{1}{L_m}\int (v_{qs}^{s} - R_s i_{qs}^{s})dt - \frac{L_s}{L_r} i_{qs}^{s}$$

$$i_{dr}^{s} = \frac{1}{L_m}\int (v_{ds}^{s} - R_s i_{ds}^{s})dt - \frac{L_s}{L_r} i_{ds}^{s}$$

The rotor fluxes can be written as:

$$\varphi_{qr}^{s} = L_r i_{qr}^{s} + L_m i_{qs}^{s}$$
$$\varphi_{dr}^{s} = L_r i_{dr}^{s} + L_m i_{ds}^{s}$$

The rotor flux equation is

$$|\varphi_r| = \sqrt{\varphi_{dr}^{s\,2} + \varphi_{qr}^{s\,2}}$$

The rotor flux equations from the current model are obtained from the following equations

$$\frac{d\varphi_{dr}^{s}}{dt} = \frac{L_m}{T_r} i_{ds}^{s} - w_r \varphi_{dr}^{s} - \frac{1}{T_r}\varphi_{dr}^{s}$$

$$\frac{d\varphi_{qr}^{s}}{dt} = \frac{L_m}{T_r} i_{qs}^{s} + w_r \varphi_{dr}^{s} - \frac{1}{T_r}\varphi_{qr}^{s}$$

### 3.2. Rotor Resistance identity

Two independent estimators of rotor flux vector of the induction motor parallel two independent equation of rotor flux vector. Equation (1) is based on stator voltages and currents, which is referred as voltage model of the induction and equation (2) is based on stator currents and rotor speed, which is referred as current model of the induction motor.

$$\begin{bmatrix} \frac{d\lambda_{dr}^{vm}}{dt} \\ \frac{d\lambda_{qr}^{vm}}{dt} \end{bmatrix} = \frac{L_r}{L_m}\left\{ \begin{bmatrix} V_{ds} \\ V_{qs} \end{bmatrix} - R_s \begin{bmatrix} I_{ds} \\ I_{qs} \end{bmatrix} - \sigma L_s \begin{bmatrix} \frac{dI_{ds}}{dt} \\ \frac{dIqs}{dt} \end{bmatrix} \right\} \qquad (1)$$

$$\begin{bmatrix} \frac{d\lambda_{dr}^{im}}{dt} \\ \frac{d\lambda_{qr}^{im}}{dt} \end{bmatrix} = \begin{bmatrix} \frac{-R_r}{L_r} & -\omega_r \\ \omega_r & \frac{-R_r}{L_r} \end{bmatrix} \begin{bmatrix} \lambda_{dr}^{im} \\ \lambda_{qr}^{im} \end{bmatrix} + \frac{L_m}{T_r}\begin{bmatrix} I_{ds} \\ I_{qs} \end{bmatrix} \qquad (2)$$

Equation (3) is the discrete form for the rotor fluxes from (2)

$$\overline{\lambda_r^{im}}(k) = \frac{TL_mR_r}{L_r} i_s(k-1) + \frac{L_r - TR_r}{L_r} I\lambda_r^{im}(k-1) + T\omega_r J\overline{\lambda_r^{im}}(k-1)$$
(3)

Where $I=\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$ $J=\begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$ $\overline{i_s}=\begin{bmatrix} I_{ds} \\ I_{qs} \end{bmatrix}$

Where equation (3) can be written as

$$\overline{\lambda_r^{nm}}(k) = \sum_{i=1}^{3} W_i X_i \qquad (4)$$

$$X_1 = \overline{i_s(k-1)} = \begin{bmatrix} i_{ds}(k-1) \\ i_{qs}(k-1) \end{bmatrix}$$

$$X_2 = I\overline{\lambda_r^{im}}(k-1) = \begin{bmatrix} \lambda_{dr}^{nm}(k-1) \\ \lambda_{qr}^{nm}(k-1) \end{bmatrix}$$

$$X_3 = J\overline{\lambda_r^{im}}(k-1) = \begin{bmatrix} -\lambda_{qr}^{nm}(k-1) \\ \lambda_{dr}^{nm}(k-1) \end{bmatrix}$$

Where the weights are

$$W_1 = \frac{TL_mR_r}{L_m};\ W_2 = \frac{L_r - TR_r}{L_r};\ W_3 = T\omega_r$$

Equation (4) is based on the model of MLPANN, Wi is the weight of MLPANN and it has to be updated using network. Xi is the input to the network. $\lambda_r^{nm}$ Is the output to the network.

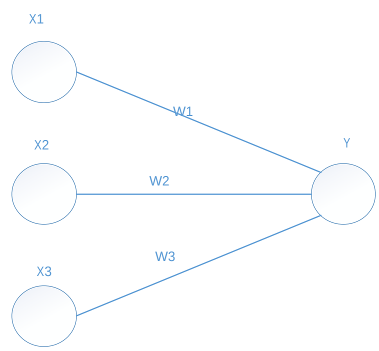


Fig 2.Structure of the neural network elements.

Here two layer network is used for the estimation of rotor resistance. First layer is called input layer which consists of three neurons fed from three inputs (i.e. X1, X2, X3). Second layer is called output layer.

Here error back propagation learning algorithm will be applied in the ANN system. The essence of the algorithm is the error from inputs will be back propagated and the weights adjustment are supplemented in the process at last the output of the estimate system will converge to the real value. The weights automatically adjust itself through the back propagation algorithm in the system.

Finally the rotor resistance can be estimated by using weights

$$R_r = \frac{L_r W_1}{TL_m} = \frac{L_r - L_r W_2}{T}$$

### 4. SIMULATION RESULTS AND ANALYSIS

The online identification of rotor resistance for vector controlled induction motor drive needs the parameters of the stator voltage, stator current and speed which was measured by sensors. The main function of observer based on

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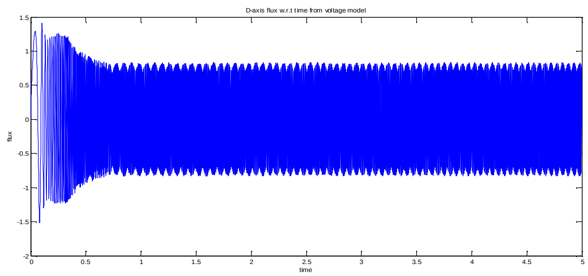
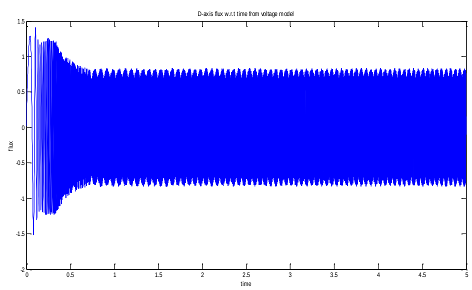
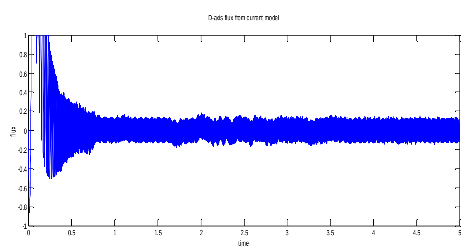
voltage model is to achieve flux observation according to the stator voltage and current signals measured by current sensors. The current model based on stator current and speed measured by sensors carried out identification of rotor resistance online by MLPANN. The parameters of the simulation model are shown in Table 1



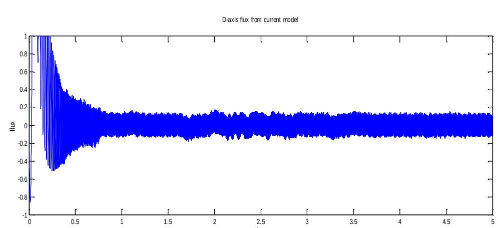

Plot of D-axis flux from voltage model




Plot of Q-axis flux from voltage model




Plot of Q-axis flux from current model




Plot of D-axis flux from current model

Rotor flux linkages from the current model compares with the output rotor flux linkages from the voltage model. If they are equal, error will be zero so weights will not be updated further. From the final weights we will identify the rotor resistance. This is the accurate value of rotor resistance. If any changes occurs in the motor parameters due to inner and outer conditions then rotor flux linkages of the motor will automatically change. This changes can be obtained from the voltage model, there by error will be generated automatically. By the back propagation algorithm the weights of the neural network will be changed in such a way that the output of the current model traces the output of the voltage model. From these weights we can find the resistance value. For the given parameters of an induction motor after 500 epochs the weight are W1=1.2834*10^-3

W2=0.9547

From these weights we can find the rotor resistance from the rotor resistance formula given earlier. During the running condition of an induction motor, the resistance is continuously varied. By using this back propagation algorithm we can identify the rotor resistance continuously.

Table1:

| | |
|---|---|
| **Rated power** | **P=1000W** |
| **Pole pairs** | **Np=2** |
| **Stator resistance** | **Rs=6.3150** |
| **Rotor resistance** | **Rr=7.1750** |
| **Stator inductance** | **Ls=413.6E-3** |
| **Rotor inductance** | **Lr=413.6E-3** |
| **Mutual inductance** | **Lm=385.5E-3** |
| **Sampling rate** | **T=20E-6** |
| **Learning rate** | **0.9** |

**Abrivations**:

IM – Induction motor

ANN – Artificial neural network

Q-axis – quadrature axis

D-axis – direct axis

## CONCLUSION

Rotor resistance changes in the performance of vector control have a significant impact. In this paper I have presented different techniques of online identification of rotor resistance for vectored controlled induction motor drives. And also this estimation was done by using back propagation algorithm. It will able to track changes in the value of rotor resistance. This will help to further research in identification of induction motor parameters by using artificial neural networks. It also provided an effective way to further enhance the performance of vector control.

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**REFERENCES**


1. T G Habetler, F Profumo, M Pastorelli and L.M. Tolbert, "**Direct torque control of induction machines using space vector modulation**", Conference Record of the 1991 IEEE Industry Applications Society Annual Meeting, Vol.1, pp.428-436, 28 Sept.-4 Oct. 1991.
2. F. Blaschke, "**The principle of fiels-orientation as applied to the Transvector closed-loop control system for rotating-field machines**", in Siemens Review 34, pp.217-22, 1972..
3. Lipo, T. & Novotny, D. (1985). **Introduction to field orientation and high performance drives**. Tutorial course,
IEEE LAS, 2.1-2.64.
4. *Ebrahimi, M., Seifi, H., Shoulaie, A. & Sarraf, H. S. (1999).* ***A software modification procedure for conversion***
**of a scalar controller to a vector type for an induction motor**. Iranian Journal of Science and Technology, 23, 11-
25.
5. H.A.Toliyat,E.Levi, and M.Raina,"**A review of RFO induction motor parameters estimation techniques**," IEEE Transactionson EnergyConversion,vol.18,no.2,pp.271–283,2003.
6. E. Foulon, C. Forgez, and L. Loron, "**Resistances estimation with an extended Kalman filter in the objective of real-time thermal monitoring of the induction machine**," IET Electric Power Applications, vol.1, no.4, pp.549–556, 2007.
7. L.-C. Zai, C. L. DeMarco, and T. A. Lipo, "**An extended Kalman filter approach to rotor time constant measurement in PWM induction motor drives**," IEEE Transactions on Industry Applications,vol.28,no.1,pp.96–104,1992
8. A. Accetta, M. Cirrincione, M. Pucci, and G. Vitale, "**Neural sensor less control of linear induction motors by a full-order Luenberger observer considering the end-effects**," in Proceedings of the 4th Annual IEEE Energy Conversion Congress and Exposition(ECCE'12),pp.1864–1871,IEEE,September2012.
9. S. M. N. Hasan and I. Husain, "**A Luenberger-sliding mode observer for online parameter estimation and adaptation in high-performance induction motor drives**," IEEE Transactions on Industry Applications, vol.45, no.2, pp.772–781, 2009.
10. K.-B. Lee and F. Blaabjerg, "**Reduced-order extended Luenberger observer based sensor less vector control driven by matrix converter with nonlinearity compensation**,"IEEETransactionsonIndustrialElectronics,vol.53,no.1,pp.66–75,2006
11. R. Blasco-Gimenez, G. Asher, M. Sumner, and K. Bradley, "**Dynamic performance limitations for MRAS based sensor less induction motor drives**. Part 1: **stability analysis for the closed loop drive**," IEE Proceedings-Electric Power Applications, vol. 143, no.2, pp.113–122, 1996.
12. S. Maiti, C. Chakraborty, Y. Hori, and M. C. Ta, "**Model reference adaptive controller-based rotor resistance and speed estimation techniques for vector controlled induction motor drive utilizing reactive power,**" IEEE Transactions on Industrial Electronics,vol.55,no.2,pp.594–601,2008.
13. M. Cirrincione, A. Accetta, M. Pucci, and G. Vitale, "**MRAS speed observer for high-performance linear induction motor drives based on linear neural networks**," IEEE Transactions on PowerElectronics,vol.28,no.1,pp.123–134,2013.
14. Y. Shi, K. Sun, L. Huang, and Y. Li, "**Online identification of permanent magnet flux based on extended Kalman filter for IPMSM drive with position sensor less control**," IEEE Transactions on Industrial Electronics, vol.59, no.11, pp. 4169–4178, 2012
15. G.Kenn´e,R.S.Simo,F.Lamnabhi-Lagarrigue,A.Arzand´e,and J. C. Vannier, "**An online simplified rotor resistance estimator for induction motors**," IEEE Transactions on Control Systems Technology,vol.18,no.5,pp.1188–1194,2010..
16. G. Kenn´e, T. Ahmed-Ali, F. Lamnabhi-Lagarrigue, and A. Arzand´e, "**Nonlinear systems time-varying parameter estimation: application to induction motors**," Electric Power Systems Research, vol.78, no.11, pp.1881–1888, 2008.
17. Lorenz, R. D., & Lawson, D. B. (1990**). A simplified approach to continuous on-line tuning of field-oriented induction machines drives** .IEEE Transactions on Industry Applications, 26(3), 420–424
18. Garces, L. J. (1980). **Parameter adaption for the speed-controlled static ac drive with a squirrel-cage induction motor.** IEEE Transactions on Industry Applications, 1A-16(2), 173–178.
19. Rowan, T. M., Kerkman, R. J., & Leggate, D. (1991). **A simple on-line adaptation for indirect field orientation of an induction machine**. IEEE Transactions on Industry Applications, 27(4), 720–727
20. B.K.Bose, "**Neural network applications in power electronics and motor drives-An introduction and perspective**," IEEE Trans. Ind. Electron., Vol. 54, no.1, pp. 14-33, Feb. 2007.