Machine model based Speed Estimation Schemes for Speed Encoderless Induction Motor Drives: A Survey

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Abstract

Speed Estimation without speed sensors is a complex phenomenon and is overly dependent on the machine parameters. It is all the more significant during low speed or near zero speed operation. There are several approaches to speed estimation of an induction motor. Eventually, they can be classified into two types, namely, estimation based on the machine model and estimation based on magnetic saliency and air gap space harmonics. This paper, through a brief literature survey, attempts to give an overview of the fundamentals and the current trends in various machine model based speed estimation techniques which have occupied and continue to occupy a great amount of research space.

Keywords: Machine Model, Adaptive Speed Observers, Extended Kalman Filters (EKF), Sliding Mode Observers, Intelligent control

1. Introduction

The essence of employing encoderless induction motor drives is to eliminate additional space and cost which would otherwise be attributed to the speed encoder. The use of speed encoders also acts contrary to the inherent robustness of the induction motors. Therefore, estimation of speed without speed sensors emerged as an important concept. Great amount of research has been done in this regard and it continues to inspire more, with the onset of artificial intelligence based speed estimation and other emerging technologies. The speed can be estimated either from the magnetic saliencies or by a machine model fed by terminal quantities. Owing to the complexity of speed estimation, the most discussed problems were the estimator's sensitivity to motor parameter changes, low and zero speed operation, speed estimation at field weakening region, stability problems in the regenerative mode etc. This paper attempts to enlighten the reader on the machine model based speed estimation strategies by analyzing existing research. It also tries to identify the best method among the various machine model based schemes discussed and provides insights for future investigations.

2. Mathematical Model of the Induction Motor

The dynamic state space model of the induction motor aids in the formulation of estimation and control algorithms. It also helps in determining the internal behavior of the system along with the desired input and output. The induction motor can be dynamically modeled by the following equations in synchronous reference frame, where the stator current and the rotor flux are state variables [12].

$$p \begin{bmatrix} i_s^e \\ \psi_r^e \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} i_s^e \\ \psi_r^e \end{bmatrix} + \begin{bmatrix} B_{11} \\ 0 \end{bmatrix} V_s^e \tag{1}$$

$$\dot{x}^e = A x^e + B v_s^e \tag{2}$$

$$i_s^e = C x^e \tag{3}$$

where,

$$x^e = [i_s^e \ \psi_r^e]^{\mathrm{T}}, i_s^e = \left[i_{ds}^e \ i_{qs}^e\right]^{\mathrm{T}}, \psi_r^e = \left[\psi_{dr}^e \ \psi_{qr}^e\right]^{\mathrm{T}}$$

The electromechanical torque is given by

$$T_e = \frac{3}{2} \frac{P}{2} \frac{L_m}{L_r} \left(i_{qs}^e \psi_{dr}^e - i_{ds}^e \psi_{qr}^e\right) \tag{4}$$

where L_m and L_r are magnetizing and rotor inductances respectively.

3. Literature Survey

Speed Estimation exploiting the concept of magnetic saliencies like rotor slot harmonics, rotor signal injection, changes in leakage reactance etc. though, independent of machine parameters, present their own set of disadvantages. The slots which are on the rotor surface induce space harmonics in the air gap flux caused due to the reluctance modulation provided by them. These induced space harmonics superimpose the fundamental flux waveform. As a result, the induced stator voltage comprises a ripple voltage component whose frequency and magnitude is proportional to the rotor speed. But, at low speeds, the variation in reluctance, being small and finite number of rotor slots, the speed estimation is not accurate. The Figure 1 shows the general classification of speed estimation methods.
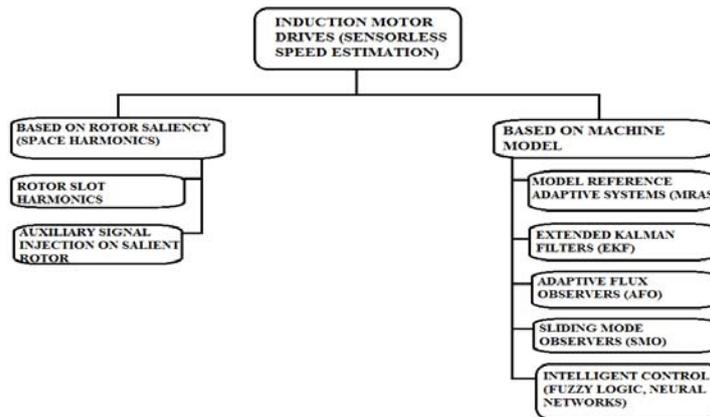

Figure 1. Classification of Speed estimation methods

In case of speed estimation based on signal injection, the rotor slots are specifically altered to get the required space harmonics and the saliency of the rotor position is determined by the position estimation algorithm. For this, a high frequency voltage component is used as a carrier signal, followed by appropriate processing combined with a closed loop observer model, tracks the rotor saliencies. The signal injection is present even at low and zero speed operation. As it can be seen, the complexity of estimation algorithm is obvious, due to the presence of many signal processing and filtering mechanisms. Again, the efficacy of the algorithm is affected by variations in load torque and inertia. On the other hand, the speed estimation from terminal quantities fed from the machine model is relatively less computationally intensive and simple. These methods display good performance at high and medium speeds. But they are not stable at very low operating speeds as they are parameter dependent and parameter errors can degrade speed performance. A simplified block diagram of a speed sensorless vector controlled induction motor drive employing the machine model based speed estimation scheme is shown in Figure 2. The more prominent configurations are presented below:

3.1 Model Reference Adaptive Systems (MRAS)

As the name suggests, an adaptive system adapts itself to the controlled system with parameters which need to be estimated or are uncertain. Unlike robust control, it does not need

any first hand information about the bounds on these estimated or uncertain parameters. The primary aim of adaptive control is parameter estimation. The MRAS forms the crux of adaptive control. The MRAS is easy to implement and has a high speed of convergence and adaptation and it also displays robust performance to parameter variations. The general configuration of MRAS is shown in Figure 3. The error vector is obtained as the difference in the outputs of the reference and adjustable models. The two models are fed from the machine terminals. The adaptive mechanism forces the error vector to zero in order to converge the estimated output to the reference output. During the design of the adaptive control scheme, special emphasis has to be laid on the convergence mechanism.
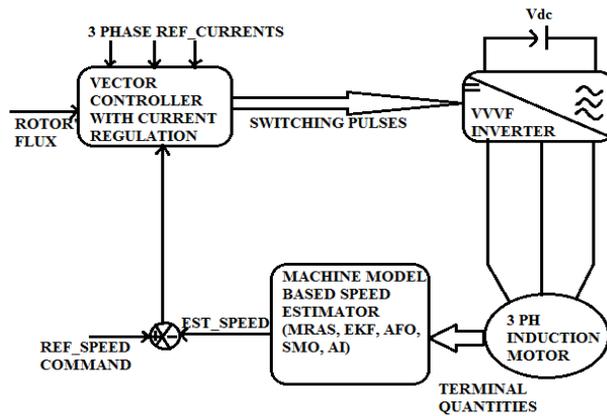

Figure 2. Speed sensorless vector control scheme

Since stability of the estimator is of great concern at all speeds, Lyapunov stability criterion plays an important role in deriving the control laws and force convergence as well as ensure fast error dynamics. Adaptive mechanisms can be in the form of fixed gain PI Regulators, Fuzzy Logic (FL), Sliding Mode (SM) based etc. Recent research focus has been to replace the classical PI controller by either Sliding mode or Fuzzy logic based adaptation schemes. Neural network concept has also been used for rotor flux observer to overcome the problems of dc drift and instability. As Sensorless Model based speed estimation methods are sensitive to machine parameters, several methods and algorithms have been proposed for parameter adaptation also, in order to optimise the performance of the drive. These algorithms involve online adaptation of parameters like the rotor time constant, stator resistance etc.
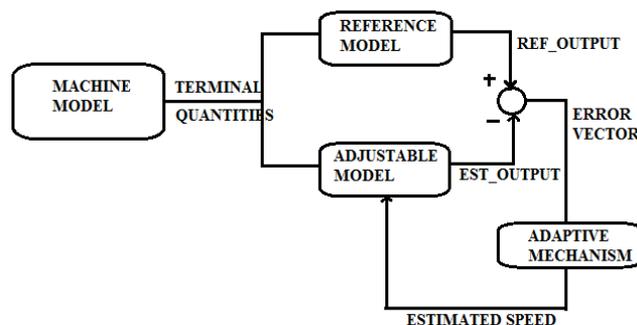

Figure 3. General Configuration of MRAS

S.M. Gadoue et al, [18] proposed the sliding mode and fuzzy logic based adaptation mechanisms to replace the existing fixed gain linear PI controller. He concedes the fact that the

PI controllers may not be able to provide the desired performance when the drive is subjected to continuous variations in the machine parameters and operating conditions. He goes on to add that the controller performance can be improved by means of employing adaptive control techniques like gain scheduling i.e., varying PI gains with the operating conditions. He also points out that more attention can be focused on different adaptation mechanisms for speed tuning. In his article, the performance of the two novel adaptation mechanisms are compared with that of the conventional one and the results are presented for both open loop and closed loop. MRAS based approach varies with the quantity that is selected as output of the reference and adjustable model. The more popular choices happen to be rotor flux, back emf, stator currents and Instantaneous reactive power. The open loop sensorless speed estimation performance of different configurations of MRAS based speed observers are shown in Figure 4. S.M.Gadoue et al, [19] has also incorporated the concept of employing a two layer, tuned neural network observer as an adaptive model for a stator current based MRAS. In his investigation, two networks are employed, the first one for estimating the stator current and the second one for estimating the rotor flux. This eliminates the traditional problems of instability and dc drift faced by either the voltage model or the current model which was used for rotor flux estimation
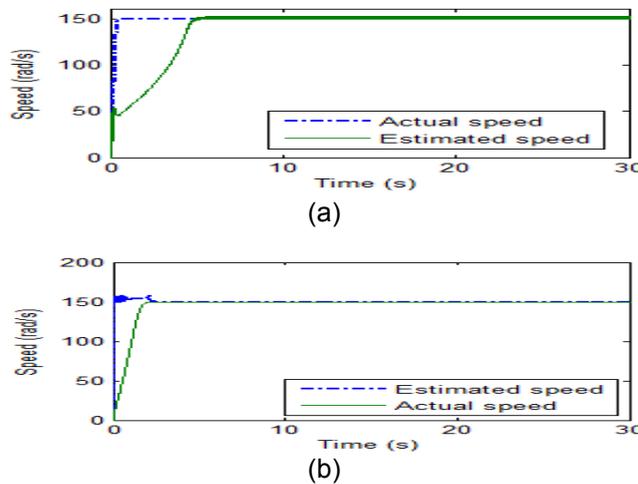

Figure 4. Speed tracking performance for Load torque perturbation of 200Nm (a). Rotor Flux based MRAS (b). Back EMF based MRAS

DP Marcetic et al, [3] observes that the performance expected of a drive in terms of the rotor speed and the fundamental frequency has gone up in view of the energy crisis and competition. But for cost and efficiency concerns, he pointed out that the increase in the fundamental output frequency of the inverter cannot be compensated with the increase in the switching frequency of the inverter, as it would give rise to high switching losses and be more computationally intensive.

$$F_{ratio}=F_s/F_{out} \tag{5}$$

But the low Frequency ratio also gave rise to problems at very high rotor speeds, prominent of them being, the integration drift and phase error in the discrete reference and adjustable models. Therefore a new discretised version of the rotor flux estimator was designed which addressed the joint problems stated above. As a result, the integration in the adaptive current model and the phase error were stabilized and cancelled out.

3.2 Extended Kalman Filters (EKF)
The Kalman filters are designed purely on non deterministic principles assuming a noisy environment. The EKF is popularly used as a full order observer for optimal state estimation of non linear systems. The utility of EKF can also be extended for the estimation of joint state and

parameter (like Rotor resistance). It is based on the linearization of a non linear dynamic model and provides accurate estimation only if the error is also linear. Therefore, the EKF algorithm has to consider several aspects such as information about the dynamics of the system, perturbations and uncertainties in the system model etc. I.M. Alsofyani et al, [9] asserts that the process of estimating the non measured parts of a linear dynamic system proceeds by achieving a minimum covariance error which in turn leads to optimal estimated states. By ensuring linearization about the recent estimated states, the non – linearity can be overcome. From [9], the discretised model of the Induction motors has the following general form:

$$\dot{x}(k + 1) = f(x(k), u(k)) + w(k) \tag{6}$$

$$f(x(k), u(k)) = A(x(k))x(k) + Bu(k) \tag{7}$$

$$Y(k) = Hx(k) + v(k) \tag{8}$$

where *f,Y,H* are non linear functions of the state variables, the input and output state vectors and the measurement matrix respectively, while the system and measurement noises are represented by *w* and *v*. The linearisation step is performed around the estimated state vector:

$$F_i(k) = \frac{\partial f_i(x_i(k), u(k))}{\partial x_i(k)} \tag{9}$$
w.r.t $\hat{x}_i(k)$

Therefore, the following equations represent the Recursive EKF Algorithm:

$$P(k) = F(k)P(k)F(k)^{-1} + Q \tag{10}$$

$$K(k + 1) = H^T P(k)(HP(k)H^T + R)^{-1} \tag{11}$$

$$\hat{x}(k + 1) = \hat{f}(x(k), u(k)) + K(k)(Y(k) - H\hat{x}(k)) \tag{12}$$

$$P(k + 1) = (I - K(k + 1)H)P(k) \tag{13}$$

where the covariance matrices P,Q and R obtain the state estimation error, system and output noises respectively. As it can be seen from the above algorithm, first, the predicted states and the predicted state covariance matrix are obtained, which consequently leads to the optimal estimated states, by adding the predicted states and the correction term (second term in (8)) in the filtering stage. The basic structure of the EKF mechanism is shown in Figure 5.
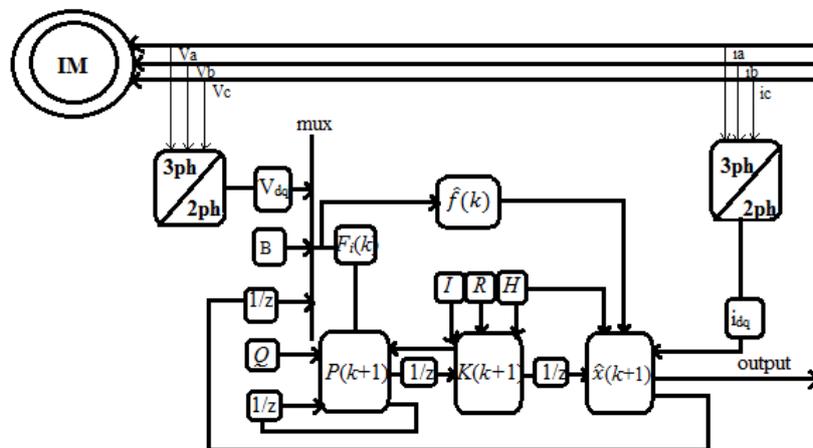

Figure 5. EKF Scheme structure [9]

All these make the implementation of the algorithm computationally intensive and warrants a very fast and digital signal processor to handle extensive amounts of information and perform complex calculations. Consequently, the online tuning and estimation of the states becomes laborius [2], [6], [8].

The recent investigations involving state estimation using EKF are discussed. As we already know, Extended Kalman Filters make use of a linearised model of a non linear dynamic system. But, S.Jafarzadeh et al, [15] proposed and implemented an unscented version of the Kalman filter (UKF). The unscented Kalman filter, simply put, is an extended version of the Kalman filter for non linear state estimation. By use of Unscented transforms (UT) in the prediction step, the algorithm tries to guage the non linear behaviour of the system directly instead of the linearised model. He proposes different variants of the UKF based on respective Unscented Transforms for Induction Motor state estimation and also discusses the theoretical analysis and implementation of the UT's. Different variants of UT's are presented for very high as well as low speed regions and comparison is also made with the traditional EKF. The authors also concede the fact that the performance of a sensorless drive depends largely on the state observer. The UT is a nonlinear function of a random variable and is based on a linear regression drawn from a chosen set of sample points known as six sigma points, which are drawn from the prior distribution of the random variable. Therefore UKF's are also called as Sigma Point Kalman filters. The combination of the concept of KF with UT determines the non linear state of the Induction Motor with relatively good accuracy and ensures better performance compared to the EKF.

F Alonge et al, [4] makes use of a reduced order KF to estimate the rotor flux, by taking into account parameter variations. The speed is estimated by means of a recursive least squares algorithm having a prior knowledge of the rotor flux. The reduced order KF has a descriptor type structure which directly translates the parameter variations into variations of coeffcents in the model. It estimates the rotor flux for a given speed. This feature improves the robustness of the state estimation subject to parameter variations. Secondly, there is no necessity for theusage of non linear state estimation methods like EKF and the determination of load torque and parameter estimation is also avoided.

3.3 Adaptive Speed Observers

H.Kubota et al, [7] proposed a Full order speed Adaptive Flux Observer (AFFO) based on adaptive control theory. The AFFO stabilises the performance of the drive even at low speed region by allocating poles arbitrarily. It makes use of either the Lyapunov's stability criterions or the Popov's criterions to derive the adaptive scheme. The AFFO, apart from estimating the Stator current and rotor flux, also makes use of a gain matrix which is used for stability purpose. But the AFO is susceptible to large scale speed errors under heavy loads and steady state speed disturbances under light load conditions. The proposed flux observer from [7] is shown in Figure 6.
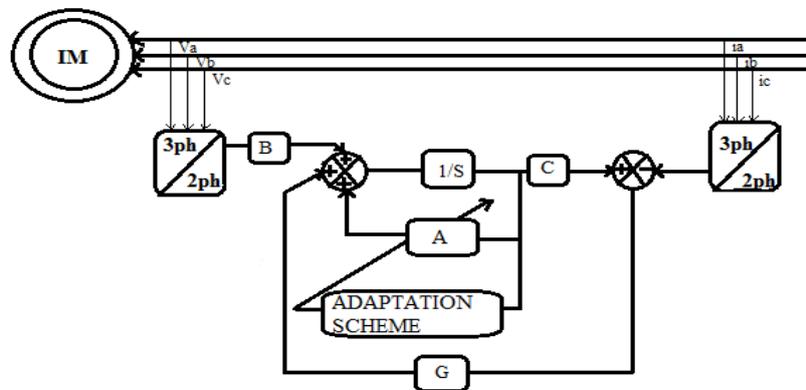

Figure 6. Adaptive Observer scheme for speed estimation [9]

The state equations are utilised to get the general equation of the observer model as shown below [7]:

$$\dot{X} = AX + BU \tag{14}$$

$$Y = CX \tag{15}$$

$$X = [i_{ds}\ i_{qs}\ \psi_{dr}\ \psi_{qr}]^T \tag{16}$$

$$Y = [i_{ds}\ i_{qs}] \tag{17}$$

$$\dot{\hat{X}} = A\hat{X} + BU + G(Y - \hat{Y}) \tag{18}$$

$$\dot{X} - \dot{\hat{X}} = (A - GC)(X - \hat{X}) \tag{19}$$

where, 'A' is the system matrix, the symbol '^' indicates estimated values, 'X' comprises the state variables which are the direct and quadrature axes stator currents and rotor fluxes, 'G' is the observer gain matrix, chosen in such a way that the Eigen values of the observer are proportional to the Eigen values of the machine to ensure stability under normal operating condition. Recent investigations have seen the AFFO's being used for joint state estimation, particularly under unstable operating conditions and zero stator frequency conditions and also the sensor count getting reduced. I.Vicente et al, [10] recognizes the significance of an AFFO for state estimation. But he concedes the inherent problems suffered by the AFFO, such as an unstable regenerative region and dc (zero frequency) conditions. Also, there is a necessity for parallely estimating the stator resistance in the low speed region which would result in a Multi input Multi Output (MIMO) system. Therefore, the authors propose to simplify the MIMO system into a Single input Single Output (SISO) system by means of a two time scale approach for the purpose of stability analysis. The analysis proceeds through a set of four different stabilization strategies based on 'augmented error signal' and 'observer gain retuning'. In order to incorporate these strategies, the simplified SISO model is considered. For aiding the estimation of stator resistance, the Induction Motor model is presented as a canonical 'Γ' equivalent model representing the stator side.

FR Salmasi et al, [5] has shown and implemented an adaptive observer which estimates online, the rotor and stator resistances by reducing the current sensor count to one. The proposed observer simultaneously estimates stator currents and rotor fluxes while, at the same time, undertake online tuning for rotor and stator resistances. The reliance on a single phase current measurement also reduces the probability of performance degradation or instability which would otherwise be caused by the usage of two or three phase current sensors. Unlike several other methods, the algorithm doesn't use switching patterns for restructuring phase currents from the dc link current, thereby eliminating the noisy dc link current feedback. All these inherent features make it possible for the observer to be incorporated in fault tolerant drive systems. The authors admit there is considerable scope for research in the state estimation using only one phase current feedback and the development of an observer in fault tolerant drive systems.

3.4 Sliding Mode and Intelligent Control Based Speed Estimation Techniques

Sliding Mode Observers (SMO), on account of their robustness have been increasingly used for specific classes of non linear tracking problems, subject to parametric uncertainties and external disturbances [11]. The Sliding mode concept, changes the dynamics of a non-linear system by means of high frequency switching (discontinuous) control laws, such that the system is forced to slide along the cross section of its normal behavior. For the system to slide along the boundaries, it needs a sliding surface (which is a loci representing boundaries) illustrated in Figure 7.
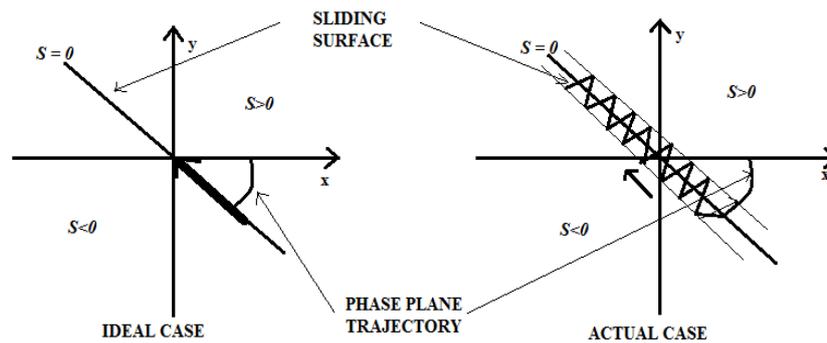
Figure 7. Sliding Surface and the Phase plane trajectory of the system

The Sliding surface varies with the nature of the system. For instance, if it's a first order system, the sliding surface is a straight line. For higher order systems, the sliding surface is more complex. The trajectory of the system as it slides along these boundaries is called sliding mode. The state feedback control law is discontinuous in nature and switches according to the existent position in the state space from one continuous structure to another. Therefore, it is also called variable structure control. It also forces the system state from any arbitrary initial state to the equilibrium state existing on the sliding surface. For implementing the concept, there are some important issues which need to be given due consideration:
- The Sliding condition (or the reaching condition) must be satisfied.
- The Error tracking is independent of variation of system parameters (Robust mechanism).
- On changing the controller gain, or boundary, there will be some oscillations (chattering) involved which are undesirable.

Therefore there is a necessity of a compensation mechanism to replace the chattering control. Consequently, the current research focuses on reducing the chattering and implements high frequency switching control. RP Vieira et al, [14] proposes a discrete time SMO for estimating the rotor speed. He also discusses traditional algorithms aimed at chattering reduction, high frequency switching, stability analysis and parameter convergence requirements. A new discrete estimation algorithm is developed. Similarly, the Induction Motor model state equations are discretised. By adopting a discrete time approach, the authors hope to relate the time sampling with the observer gain to ensure stability. The existence of the switching plane is discussed and the bounds of the Sliding mode control in relation to the Induction motor parameters, sampling time and current estimation error are presented and analyzed. Traditional algorithms to reduce the chattering control are also employed. Figure 8 shows the sliding mode scheme for speed estimation. The Low Pass Filter is used to reduce the chattering phenomenon. Artificial Intelligence based speed estimation techniques have also forayed into the research domain recently. Primarily, Artificial Neural Network (ANN) and Fuzzy Logic (FL) have been used as adaptation mechanisms. Fuzzy Logic controllers, being cheaper to develop, have a wide operating range and since Fuzzy has the habit of approximation, it is easier to interpret it. The use of appropriate rule bases also makes it easily understood by humans [13].

A typical Fuzzy Logic controller comprises of the following elements:
- Fuzzification block – Captures the input data and   converts   it into a fuzzy set.
- Rule Base – The fuzzy rules are applied to the given input. Based on the rules and logic, the interference part makes the decision. Mostly, the Mamdani type rule base is used for decision making.
- Defuzzification – The processed input is converted into non-fuzzy output which then is sent to the control environment.
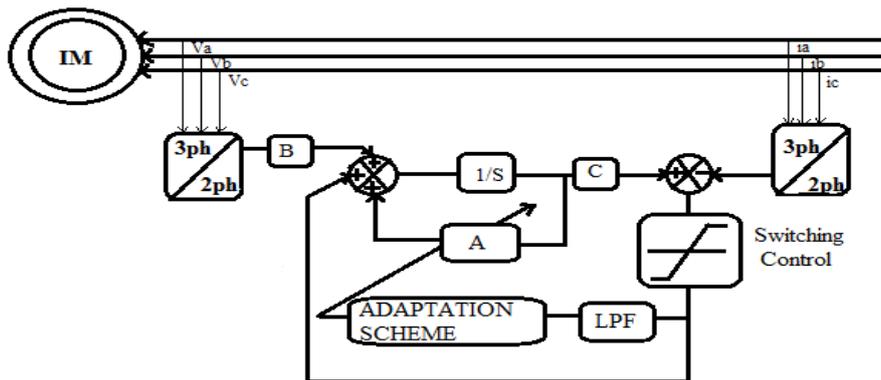
Figure 8. Sliding Mode observer scheme for speed estimation (I.M. Alsofyani et al, 2013)

S.M.Gadoue et al, [18] implements a Mamdani type rule base with the inputs being the speed tuning signal and its change. By means of appropriate scaling factors and discretisation; the actual value of the estimated speed is obtained. An equivalent PI type FL controller is designed. The authors note that the selection of scaling factors play a significant role in the performance of the FL controller.

The Artificial Neural Network (ANN), similar to Fuzzy mechanism, is widely considered for approximation in the domain of non-linear control. The Neural networks are typically organized in layers comprising of the input, output and hidden layers. The actual processing is done in the hidden layers via a system of weighted connections [17]. The hidden layer, generally, uses sigmoid shaped activation functions and the output layer uses a linear function. One can choose the neural network depending upon the parametric uncertainties and observer non-linearities [1]. The design procedure of ANN has particularly evinced keen interest and many algorithms have been developed for the training of the linear neuron. S.Maiti et al, [16] implements a scheme in which the adjustable model of a Reactive power based MRAS is modified through ANN, to cater to stability improvement under regeneration. The structure of a neural network is illustrated in Figure 9.
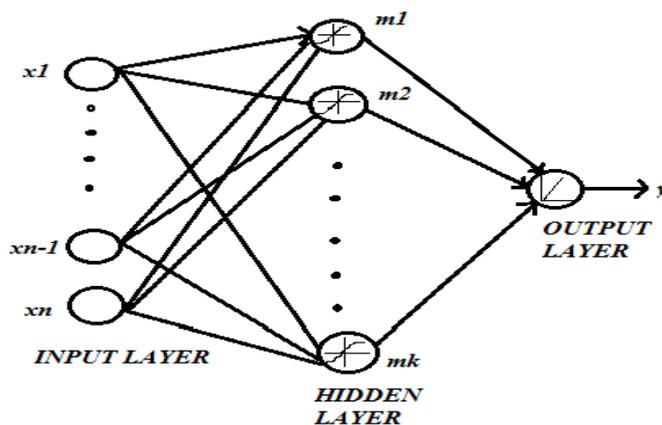

Figure 9. Neural Network Structure

By selecting the appropriate input and output training sets, the Neurons in each layer and the number of hidden layers, the authors propose the following performance indices for selection of ANN architecture.
- Least Mean Square error (LMSE) for judging the performance of the trained ANN.
- Speed Estimation Error (transient and steady state).

-    Size of ANN (Total number of neurons).

In order to make it less computationally intensive, the total number of neurons is assigned a modest value of 20.

4. Discussion

Several inferences and observations can be drawn based on the above speed estimation methods. There is a clear unanimity amongst most of the authors that the behavior of the entire control system is largely dependent on the behavior of the state estimator. For this purpose, robust design techniques can be incorporated for the design of either the controller or estimator. It is also observed that the speed estimation performance at very low operating speeds in the vicinity of zero stator frequency still remains a research problem. While speed estimation using single phase current sensor is an emerging research area, the rotor and stator resistance estimation with the single current feedback needs to be explored more. The above concept can also be incorporated for the development of fault tolerant drive systems. It is also noticed that the EKF mechanism, though accurate, requires a high sampling frequency at the expense of computing space. Extensive research has been reported on MRAS based speed estimation schemes as they are easily implementable and occupy less computing space compared to other algorithms. Recent research has seen the traditional PI type controller being replaced by either Fuzzy Logic or ANN based controllers. Though Sliding Mode adaptive mechanism is very effective against all sorts of disturbances, the problem of chattering still persists. Several studies to reduce the chattering effect in sliding mode based speed estimation schemes can also be undertaken. The current research trends also focus more on MRAS with Lyapunov stability criterion, an extended Luenberger Observer and Online parameter adaptation.

5. Conclusion

The different Speed estimation schemes for speed sensorless induction motor drives have been highlighted with greater focus on machine model based schemes. Through a brief literature survey, the study tries to capture the recent and the relevant trends in this particular domain. Relative merits, limitations and scope for further research has also been discussed. Also, various issues with respect to speed estimation, such as stability of the estimator at low operating speeds, unstable regions, and parametric uncertainties have also been emphasized.

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