Chapter Two

REVIEW OF RELATED LITERATURE

Chapter 2 provides a discussion on previous papers that are related to this study. This serves as a reference on papers that have previous discussions on Field Oriented Control, Sensorless FOC Observers, Model-based Observers, and Neural Network Observers. This chapter also provides a summary of previous observers implemented using neural networks.

2.1 Field Oriented Control

The concept of vector control was first introduced by [25]. This was applied as a special consideration on torque generation and control when rotating-field machines are employed as drive motors. This paper proposes a new principle of field orientation as a new closed-loop control method for such machines. In referencing an induction motor there are manipulated variables that should be influenced for the closed-loop control.

Also, [26] emphasized on the increasing scale of the utilization of synchronous machines in industrial drive systems. Therefore, the drives for these synchronous machines should offer high-grade dynamic characteristics. An emphasis was also made on having a provision to control the torque instantaneously to a linear curve relationship, and not only on torque but also on the magnetization of the synchronous motor itself. One important aspect of the proposal was that both control operations should be decoupled wherein one control loop will influence only the torque – and effectively the active power, and the other will cover only the magnetization – and therefore the reactive power.

2.1.1 Direct and Indirect FOC

Developments in the field of power electronics have introduced more applications for field-oriented control. [27] discussed the classification of FOC control as direct or indirect, direct making use of the magnitude and angle of the rotor flux which is either measured or estimated via a flux estimator, indirect making use of a Feedforward path in determining the rotor flux position. In this paper, [27] compared indirect field-oriented control with another technique, field acceleration method (FAM). The paper concluded that the two methods introduced by [25] and Yamamura [28] respectively, were identical.

2.1.2 Different Implementations of Field-Oriented Control

Significant developments on the design and implementation of field-oriented control for synchronous motors have been made after the pioneer papers. In [29], different control strategies or implementations of FOC were given a relative comparison for the ease of selecting an application – appropriate method by way of providing the drawbacks and advantages of each.

Electric motors or more specifically induction motors consume a considerable amount of power especially when scaled up for industrial applications. For field-oriented control, [30], proposed a practical method to achieve optimal efficiency for a variable speed drive. This method is used over the complete operating range. [30] introduced a method for maximum efficiency control that does not require exact knowledge or value of the machine/motor parameters – which poses a challenge in real applications. The proposed method adaptively adjusts the flux level using field-oriented control along with the measured input power of the system.

2.1.3 Advantages of Field-Oriented Control over Direct Torque Control

[31] outlined the detailed comparison between field-oriented control and direct torque control (DTC). Indirect FOC is preferrable than direct FOC in sensorless operations. Any flux estimator can be implemented by using indirect FOC [32]. Table 2.1 provides a detailed comparison between FOC and DTC based on [31].

Table 2.1 Performance comparison between FOC and DTC

	FOC	DTC	Operating Conditions
Steady-State Performance	FOC has lower values for three-phase rms current ripple vs DTC	DTC produces a relatively higher three-phase rms current ripple vs FOC	Rotor Speed Values of 100%, 50%, and 10% of the rated value. Torque Values of 100%, 50%, and 10% of the rated value.
	FOC has lower amplitude for torque ripple vs DTC	The oscillations in the torque ripple are more regular and uniform in DTC vs FOC	
	Based on the torque ripple's harmonic spectrum, FOC's harmonics corresponds to the period of the modulation cycle	DTC's spectrum produces a series of harmonics with lower values distributed over the frequency range.	
	FOC generates a high frequency uniform noise according to the current spectrum.	DTC produces an irregular noise level according to the current spectrum.	
Transient Performance	FOC has a delayed torque response due to the use of PI controllers.	DTC has a better torque response in terms of settling time and maximum overshoot.	Torque Step Variation from 0 Nm to 26.5 Nm (rated torque) at different rotor speeds.

2.2 Sensorless Field-Oriented Control / Observers

A significant amount of research has been conducted on implementing sensorless field-oriented control. The requirement on the instantaneous data on the rotor/shaft speed and/or position requires sensors be placed in the motor itself causing significant challenges. [33] proposed a sensorless control method specifically applicable for field-oriented control that does away with the shaft sensor that provides information on the rotor speed.

2.2.1 Advantages of Using Sensorless Field-Oriented Control

Conventional Field-Oriented Control that requires transducers present a significant challenge in the implementing FOC in a wider range of applications. There are numerous situations wherein the use of a rotational transducer puts the designer at a disadvantage such as hostile environments for motor drives, high-speed motor drive applications, and these situations are aggravated by the complexity of adding mechanical sensors as well as their being fragile [34][35][36].

General application of sensorless FOC specifically in commercial appliances attempt to address high costs aggravated by the additional sensors or transducers required by conventional FOC and try to reduce the physical or mechanical space that the motor consumes or the encumbrance, which is also affected by the presence of the transducers [2][37][38].

2.2.2 Challenges of Sensorless Field-Oriented Control

Sensorless implementation of FOC does come with its disadvantages. Implementations of sensorless FOC by drive algorithms based on the direct and quadrature (d-q) equivalent of the induction machine are dependent on the machine or motor parameters and the accompanying measurement errors [39].

Since most estimators are based on the model of the motor, the selection of the motor's parameters' values become critical to the overall accuracy of the control method. Estimation errors in the motor/machine's parameters induce a significant offset on the estimation process for the rotor speed or position [33][40][41].

Challenges in estimation of the rotor speed and position arise at low- and zero-speed operations. The fundamental frequency model being used in most estimators have a higher accuracy at high-speed operations but will have degraded performance or increased errors at low- and zero-speed operation as measured parameters such as the stator voltage become increasing low [41][42][43].

2.2.3 Implementations of Sensorless Field-Oriented Control

Multiple implementations for sensorless FOC have been proposed throughout the past two decades. Each attempting to address the various deficiencies that the sensorless control method is challenged with. The implementations for sensorless induction motor drives can be distinguished into two major categories. The first being rotor-saliency based techniques [2] or is also referred to as rotor slot harmonics and high-frequency signal injection methods [4]. The second category for estimation method depends on the motor model or is considered as model-based estimation.

2.3 Model-based Observers

2.3.1 Model Reference Adaptive System

Estimation of rotor speed and position can be achieved by using two motor models simultaneously. This method utilizes the Model Reference Adaptive System (MRAS). The error vector for estimation is generated from two models of the motor which are based on two different motor parameters. MRAS is advantageous to use in induction motor applications due to its relative simplicity and ease of application [35][44].

According to [3], MRAS-based speed estimators can be classified into three groups:

a. Classical MRAS speed estimator – a technique based on the error calculated from the rotor-flux estimations using the voltage and current models of the induction motor.
b. Back electromotive force (back EMF) based MRAS – a technique that utilizes the error between the back-EMFs estimated and calculated values.

c. Stator-current based MRAS – a technique that generates the error between estimates of the stator current via stator current model and the measured value.

Since MRAS, similar to other observers to be discussed, are dependent on some motor parameters, it becomes highly sensitive to variations in the values chosen and therefore would increase the relative difference between the actual motor parameter values. MRAS estimators are faced with challenges in terms of operating at low frequencies or rotor speed.

[45] proposed a simultaneous estimation method for the rotor flux and the rotor resistance to address the variation in the resistance parameter based on MRAS. [46] proposed an optimally tuned MRAS that is based on back-EMF that addresses the drawbacks of using pure integration is speed estimation that causes issues to initial condition estimations as well as drift. [47] proposed using an instantaneous reactive power-based MRAS scheme to address issues in the robustness of MRAS methods to motor stator resistance variations as well as the issue of using pure integrators. Improvements to overcome the disadvantages of using MRAS are proposed by [48] using a novel integrator scheme. [47] proposed a novel MRAS speed estimator that uses an adaption mechanism design aimed at having better robustness against motor parameter variations using model predictive controllers.

2.3.2 Extended Kalman Filters

Challenges that face the implementation of sensorless FOC are given a stochastic approach with the use of extended Kalman filters (EKF) or also referred to as extended stochastic observers. EKF approaches the sensorless implementation by simultaneously estimating the motor state and parameter/s.

EKFs are advantageous to use for sensorless FOC due to its stochastic nature that allows the estimator to address model uncertainties and nonlinearities that are common issues in sensorless implementation. Also, EKFs are known for having a high rate of convergence that is associated with an improvement in the system's transient response and performance [49].

However, EKFs are deemed to have high computational cost. [50] proposed an effective implementation of extended Kalman filters that aims to reduce the computational complexity of conventional EKF algorithms. The proposed EKF implementation is based on having a two-stage Kalman estimator – this type of approach is less complex than conventional implementations. Further, [51] proposed an extended complex Kalman filter that utilizes the complex-valued model of an induction motor that consequently allows faster computation with a substantial 35% reduction in the required computation time.

Aside from having high computational cost, EKF implementations that simultaneously estimate motor state and parameters have a high memory requirement for their embedded applications. As such,[52] proposed a Bi input-EKF that addresses this issue by reducing required memory area of previous studies by half.

2.3.3 Luenberger Observers

In observers that use a speed sensorless flux-oriented control, delays are introduced by low-pass filters that are used to eliminate error in speed estimation. Luenberger observers are also known to be implemented due to its performance, simplicity, and stability. [53] Similar to other estimation techniques, the performance of Luenberger observers are also affected by variations in the motor parameters due to errors, temperature, and saturation [54].

[55] proposed a speed estimation scheme for proper operation in the field weakening region. This proposed scheme replaces the LPF with the Luenberger observer to achieve accurate estimation during transient conditions.

[53] introduced a sensorless indirect stator-flux-oriented control (ISFOC) that simultaneously estimate the speed, flux, and stator currents. The speed estimator makes use of an adaptive Luenberger observer as it is one solution on estimating motor state and unknown parameters simultaneously.

More complex or advance methods of computation are implemented on the Luenberger observer to address parameter uncertainties. [54] made use of Adaptive Fuzzy

Luenberger observer to consider the rotor resistance uncertainties in the computations of the estimator.

2.3.4 Sliding Mode Observers

Another popular method for estimating rotor speed and/or position is the sliding mode observer (SMO). SMO implementation of sensorless FOC also uses the motor's model in estimation. SMO is incorporated to establish convergence of an observer's error to zero to determine an unknown parameter such as the rotor flux or the back-EMF. The use of sliding-mode observers is widely considered for sensorless operation given its robustness to system disturbances, variations on the motor's parameters, and noise present in the system [38].

As with other sensorless implementations, conventional SMO comes at a disadvantage when it comes to chattering which is inherent in a sliding mode operation. Also, the switching operation in an SMO ultimately results to the generation of high-order harmonics [56][57].

Back EMF based SMO implementations deliver on the robustness against deviations in stator resistance among others. Iterative SMO implementations attempt to address the chattering issue. [58] proposed a novel SMO for rotor position estimation that is effective over a wide range in an implementation that is capable of running in cost-effective controllers. [56] proposed an iterative flux SMO for sensorless control. The flux estimator, with its expansion of the motor state equations, is designed to eliminate the high-order harmonics while the implementation of the SMO iteratively is designed to address the chattering inherent in SMO implementations.

SMOs that are designed and modeled to estimate the rotor flux are also consistently proposed. [38] presented an adaptive sliding-mode observer for FOC that determines the rotor flux components that proves to be effective having robustness against motor parameter variation as its main advantage. [59] proposed a flux-based SMO than uses the current model of an induction motor that removes the discontinuity that is present in conventional SMO implementations, as well as decoupling the motor equations. This proposal also minimizes the effect of the rotor resistance on the current and flux equations resulting into the system's robustness against parameter variations. [60] also proposed a SMO that estimates the rotor flux at an unknown load torque condition that utilizes a combination of FOC concepts and a robust sliding mode technique.

Another attempt to reduce the effect of motor parameter variations, specifically the stator resistance, is [4] wherein the proposed sliding mode observer incorporates an online parameter identification scheme that can accurately estimate over a wide speed range from zero to values beyond the base speed. Also, this proposal incorporates a variable-structure control with Lyapunov's stability theory and Popov's hyperstability theories. Instability issues that are observed in adaptive flux observers were investigated by [61], wherein the proposed adaptive flux observer was designed with an observer feedback gain that showed a relative improvement in the system convergence and stability.

Combining a high-order sliding mode observer and a quadrature phase-locked loop (QPLL) is proposed by [62] to provide improvements on the performance of position estimation for sensorless interior permanent magnet synchronous motor (IPMSM) vector drives. In this proposal, QPLL extracts the position information directly compared with a conventional PLL that results in the non-requirement for preprocessing and the advantage of ease of application.

2.4 Neural Networks in Sensorless Observers

Implementing Neural Networks in field-oriented control of induction motors was proposed by [63]. In Song's proposal, a neural network is used for adaptive current control and not for estimation of motor state or parameters. [64] also proposed an adaptive neural network paired with a current controller for FOC. These proposals provided an improved performance against classical methods at the time such as ramp and hysteresis controllers. Although they dwelled on the implementation of neural networks on the controller aspect of FOC, it introduces neural networks in improving transient response and motor parameter deviations.

2.4.1 Feedforward Neural Networks

Toh et al. [12] proposed a Feedforward neural network for estimating the flux magnitude and position in an induction motor that is implementing FOC. In this study, it is found that using just two hidden layers in a FF network can provide a closer tracking of the flux.

[65] recognized that neural networks provide a great degree of robustness and fault tolerance as well as nonlinearities which are inherent in model-based estimation for motor sensorless control. A baseline estimator was set by using a simple perceptron as the NN. The proposal was a three-layer NN speed estimator that is used for FOC of an induction motor. The Error Back Propagation (EBP) algorithm was used for pre-training the NN and proving that NN has the potential to provide an attractive solution for sensorless speed estimation of induction motors.

In [66] compared two Feedforward neural networks for flux estimation where both have the sane internal architecture but differing in the network inputs wherein the first network uses 4 inputs: est. torque, measured speed, est. rotor resistance variation, and estimated mutual inductance variation, and the second network uses only 3 inputs: est. torque, measured speed, and est. rotor resistance variation. It is found that the mutual inductance variation of a motor proves irrelevant in an estimator’s performance when used as an input for the NN. [16] also proposed a FF neural network that estimates the rotor flux using the calculated flux and measured current as inputs. In [18], a NN was used to estimate motor torque, speed, and flux and was compared with the performance of a DSP estimator and it was concluded that the proposed NN outperforms the DSP. In [67] a multilayer perceptron network was proposed to estimate the induction motor’s torque and speed using backpropagation as the training algorithm. The practical approach was achieved as a portable and practical implementation by cascading two artificial neural networks. Similar proposals were made in [17] and [68] wherein the latter provided a comparative study between single layer and multilayer neural networks.

[19] proposed a multi-layer perceptron model that uses backward diffusion algorithm for its learning algorithm to estimate the speed of the rotor. It also stated that trial-and-

error was used in determining no of layers and neurons as there is no definite criterion in the selection of these parameters.

[21] proposed a Feedforward neural network for flux estimation alongside a single neuron adaptive method for estimating the speed. In this method, the model reference adaptive system solution was improved to be more robust to the sensitivity of motor parameters by using neural networks.

2.4.2 Recurrent Neural Networks

Rotor flux and speed estimation by using various structures of the Feedforward and recurrent neural networks were presented by [13]. Feedforward artificial neural networks (FF – ANN) uses the outputs of the plant i.e., the stator currents, in few previous steps as the neural network's inputs, while the use of a recurrent network, with a feedback loop, takes in the estimation of the network itself as the inputs. For the condition of variations in the rotor parameters, the recurrent network provided the best solution for sensorless estimation. [14] proposed an implementation using a 4-layer perceptron neural network that takes into consideration the effect of saturation in the air gap flux that contributes to the non-linear parameter variation of the induction motor.

[22] proposed using a recurrent multilayer neural network (RMNN) for sensorless speed estimation as ANNs have the ability to learn in terms of estimations in a nonlinear systems field proving to have high precision and good dynamic performance.

[69] proposed a dynamic recursive neural network for speed estimation. A complete recursive neural network was used along with fuzzy techniques to regulate the learning procedure of the network to have a faster learning rate and an improved overall neural network weight training. The fuzzy backpropagation method was used to improve on the conventional backpropagation training algorithm. This method is also applicable not just in speed estimation but also when torque is estimated.

2.4.3 Diagonal Recurrent Neural Networks

[70] proposed an adaptive estimator that utilizes two recurrent neural networks (RNN) to estimate rotor flux and speed, as well as an estimated stator current. Online adaptive

estimation is achieved by using a recursive prediction error algorithm. The proposed network utilizes the diagonal RNN architecture.

2.4.4 Orthogonal Activation Functions

[71] presented the use of orthogonal activation functions for neural networks (OAFNN) as virtual sensors, or NN used to estimate state variables, in the estimation of the rotor speed in sensorless FOC implementations. Chebychev orthogonal polynomials are used as the activation functions for the input neurons.

2.4.5 Linear Neural Networks

[72] introduced improvements on the TLS EXIN Neuron for use in flux estimation in FOC applications. The use of linear neural networks that are trained using a neural adaptive algorithm for better performance in multiple working conditions. In [73], another adaptation of the previous work is done to estimate rotor speed by using a reduced order observer using minor component analysis techniques. In [74], [75], and [76], an MRAS approach that is based on Neural Networks for speed estimation was proposed. This model takes into considerations the effects of using a linear induction motor (LIM) and implements the linear neural network to reproduce induced part equations of the current model of the LIM, also, both offline and online methods of updating the values of weights are used in this paper.

2.4.6 Radial Basis Function Neural Networks

[77] proposed a novel position control algorithm that uses the radial basis function (RBF) fast terminal sliding mode control (FTSM) to achieve good performance of tracking the position of a PMSM. This algorithm compensates the errors of network approximation and provides a solution on the dependency on motor parameters when using fast terminal sliding mode for the controller design.

In [20], a Feedforward neural network performance was compared with a RBF neural network for speed estimation. In both network architectures simulated, trial and error was used to determine the effective number of layers and neurons for the best performance in speed estimation. The RBF network with a denser structure prove to have the best relative behavior but would need to be compensated with a controller of higher performance and capacity.

2.4.7 Summary of Neural Network Studies

Table 2.2 summarizes relevant studies on neural network estimators. Also included are the network architectures used, number of layers, number of neurons per layer, and the training algorithm.

The neural network estimators presented vary in terms of the architecture, the neural network input/s, the parameter being estimated, and some hyperparameters such as the no of layers and the neurons they contain, and the learning algorithm as well. Majority of the architectures presented are feedforward in nature [11-21][67], similar to the proposed neural network estimator. The variance in terms of the neural network inputs range from the stator currents and/or voltages [11][12][13][17][18][19][20][21][67][70][71], while some use additional parameters such as the Frequency and Speed [14], and the torque, speed, Rotor Resistance Variation, and Mutual Inductance Variation [15]. The proposed neural network estimator in this study will use the stator currents and voltages as the input. One significant factor also considered is the target parameter for estimation. The proposed GA-optimized neural network focuses on speed and position estimation. While some of the previous neural network estimators estimate other parameters such as the flux [12][13][15][16][18][21], and the torque [18], others have already targeted either the speed [17][19][20][21][22][67][69][70][71] or position [11][14].

Table 2.2 Summary of Neural Network Estimators

Author	Architecture	Neural Network Input/s	Estimated Parameter	No of Layers	No of Neurons	Learning Algorithm
[12]	Feedforward	Stator Currents	Rotor Flux	4	2-20-10-1	Gradient Descent
[13]	Feedforward	Stator Currents	Rotor Flux	4	2-15-7-1	Backpropagation with Levenberg-Marquardt
	Recurrent NN	Stator Currents	Rotor Flux	4	2-15-7-1	Backpropagation with Levenberg-Marquardt
[14]	Feedforward	Stator Voltages; Stator Current; Frequency; Speed	Rotor Position	5	5-10-10-5-1	n/a
[70]	Diagonal RNN	Stator Currents and Voltages	Stator Current Rotor Speed	n/a n/a	10-n/a-1 8-n/a-1	Recursive Prediction Error Algorithm
[71]	OAF NN	Stator Currents and Voltages	Rotor Speed	n/a	n/a	Gradient Descent
[15]	Feedforward	Torque; Speed Rotor Resistance Variation; Mutual Inductance Variation	Rotor Flux	3	4-5-1	Backpropagation with Levenberg-Marquardt
[16]	Feedforward	Calculated Flux Stator Currents	Rotor Flux	3	4-13-2	Backpropagation
[17]	Cascaded Feedforward	Stator Currents and Voltages	Rotor Speed	4	4-5-25-1	Backpropagation
[22]	Recurrent NN	Stator Current	Rotor Speed	4	1-10-10-1	Gradient Descent
[67]	Feedforward	Stator Currents and Voltages	Rotor Speed	4	4-5-10-1	Backpropagation
[18]	Feedforward	Stator Currents and Voltages	Rotor Flux	4	4-12-28-2	Backpropagation with Levenberg-Marquardt
	Feedforward	Stator Currents and Voltages	Torque	4	4-8-16-3	Backpropagation with Levenberg-Marquardt
[69]	Recurrent NN	Stator Currents and Voltages	Rotor Speed	3	5-6-1	Fuzzy Backpropagation
[19]	Feedforward	Stator Currents and Voltages	Rotor Speed	3	2-4-1	Error Backward Diffusion Algorithm
[20]	Feedforward	Stator Currents and Voltages	Rotor Speed	3	8-28-1	Backpropagation with Levenberg-Marquardt
	Radial Basis Function NN	Stator Currents and Voltages	Rotor Speed	3	8-330-1	Forward Subset Selection
[21]	Feedforward	Stator Currents and Voltages	Rotor Flux	4	4-6-1	Backpropagation
[11]	Feedforward	Stator Currents and Voltages	Rotor Position	4	4-4-4-2	Backpropagation with Levenberg-Marquardt