Chapter One

INTRODUCTION

1.1 Background

In recent years, permanent magnet synchronous motors (PMSMs) have managed to gain an increased amount of research interest given its efficiency, flexibility in terms of speed, and cost-effectiveness [1]. Multiple control methods are presented to execute efficient and robust control of PMSMs. However, some of these methods require information such as the rotor speed and position which are accurately retrieved using mechanical sensors in the shaft of ac machine drives. But with the introduction of sensorless methods, there is the advantage of reducing cost and increasing the motor control system's ruggedness and reliability [2]. In proposed models used for PMSM speed and position estimation, there are model-based [3] and rotor-saliency-based techniques [2][4]. These models, however, require certain information regarding the PMSM used, examples are the stator resistances and stator inductances, among others.

Since model-based sensorless drives are very dependent on the motor parameters, variations or tolerances from the nominal value can affect the performance of the motor based on the decreased accuracy of the estimator which is an undesirable effect [5]. Certain methods have also been developed to address variations in the motor parameters including the use of model-reference adaptive models (MRAS) [2][6][7]. These MRAS-based solutions for parameter deviation is incorporated in the sensorless estimation method being used. However, when the speed and position estimator is modeled based on artificial neural networks, the compensation for the deviation in motor parameters are embedded in the estimation model itself as demonstrated in [8][9][10][11].

The use of neural networks in position and/or speed estimation is another popular method used along with MRAS, SMO, Luenberger Observers, among others. Different network architectures have been implemented in rotor speed and/or position estimators such as feedforward [11-21], recurrent [13][22], linear [23], and radial basis function[20] demonstrating advantages such as high estimation accuracy and good dynamic performance [22]. [11] proposed a neural network-based speed and position estimator that replaces the sliding-mode observer in conventional applications, providing accurate estimations without dependence on the motor parameters. However, most of the research on neural network-based estimators in FOC have relied upon a trial-and-error method in determining the best hyperparameters including the number of neurons and layers in their proposed neural network architectures, while others have failed to identify the methods used in determining these hyperparameters.

Genetic Algorithm in hyperparameter optimization in other applications have resulted to improvements in the neural-network's adaptive ability and generalization [24]. In this study, genetic algorithm is proposed to be used to optimize the hyperparameters of an artificial neural network that serves as a PMSM rotor's speed and position estimator.

1.2 Prior Studies

Prior studies considered to be relevant or related are tabulated in Table 1.1. The related studies are categorized into four subtopics: Field-Oriented Control, Sensorless Field-Oriented Control, Model-based Observers, and Neural Networks in Sensorless Observers.

Studies under Field-Oriented Control cover the comparisons between direct and indirect FOC, the different implementations of FOC, and the comparison between FOC and direct torque control. Sensorless FOC is given emphasis next, with studies expounding on the advantages of sensorless FOC, the challenges that sensorless FOC faces, and the different implementations of sensorless FOC. Studies on Model-based Observers are also included highlighting different conventional and established observers such as the model reference adaptive system, the extended Kalman filter, the Luenberger observers, and lastly, the sliding mode observers. The most relevant studies considered are those of the neural networks in sensorless observers. Different implementations of neural networks as estimators or observers for rotor speed and/or position paints the different approaches made. Different architectures are considered but none has established an optimization method for the neural network hyperparameters. Relevant studies have stated that in determining these hyperparameters, relative experimental results were used to determine the hyperparameters in their proposed models.

Table 1.1 Prior Studies

Topics	Sub-topics	References
1. Field-Oriented Control	1.1 Direct vs. Indirect FOC	[25][27][28]
	1.2 Implementations of FOC	[29][30]
	1.3 Advantages of FOC	[31][32]
2. Sensorless FOC / Observers	2.1 Advantages of Using Sensorless FOC	[2][34][35][36][37][38]
	2.2 Challenges of Sensorless FOC	[33][39][40][41][42][43]
	2.3 Implementations of Sensorless FOC	[2][4]
3. Model-based Observers	3.1 Model Reference Adaptive System	[3][35][44][45][46][47][48]
	3.2 Extended Kalman Filters	[49][50][51][52]
	3.3 Luenberger Observers	[53][54][55]
	3.4 Sliding Mode Observers	[4][38][56][57][58][59][60][61][62]
4. Neural Networks in Sensorless Observers	4.1 Feedforward Neural Networks	[11][12][13][16][17][18][19][21][65][66][67][68]
	4.2 Recurrent Neural Networks	[13][14][22][69]
	4.3 Diagonal Recurrent Neural Networks	[70]
	4.4 Orthogonal Activation Functions	[71]
	4.5 Linear Neural Networks	[71][72][73][74][75][76]
	4.6 Radial Basis Function Neural Networks	[20][77]

1.3 Problem Statement

Sensorless motor control have presented already presented multiple advantages but are still reliant on motor parameters when they are model based. Neural network-based estimators have the advantages of determining the parameters via learning. The main problem considered in this study is the time and effort in optimizing the hyperparameters of a neural network for motor position and speed estimation that are, in most studies, based on a trial-and-error method or based on previous simulations. There is also the possibility that the parameters used by past studies do not coincide with the minima of the cost function leading to lower accuracies.

1.4 Objectives

1.4.1 General Objective

The general objective of this study is the development of an optimized artificial neural network-based estimator for motor speed and position for a field-oriented control-based permanent magnet synchronous motor using genetic algorithm.

1.4.2 Specific Objectives

1. To develop the proposed neural network model in a MATLAB/Simulink environment
2. To simulate, train, and optimize the proposed model in multiple steady-state and dynamic loading conditions
3. To optimize the hyperparameters of the ANN-based speed and position estimator using genetic algorithm
4. To compare the performance of the proposed optimized model to conventional models such as the MRAS, SMO, and other NN-based estimators.

1.5 Significance of the Study

The improvement in neural network estimators contributes to increasing the viability of intelligent systems in these applications. By providing a method for optimizing the hyperparameters, better performance can be achieved further improving the performance of the network easing the burden on the developer.

This study delivers its contributions to the improvement of sensorless motor control that translates to better robustness and efficiency that are significant in applications such as unmanned aerial vehicles (UAVs). A more accurate method of estimation can translate to the better performance of the field-oriented control that could in-turn increase the motor drive efficiency. Higher efficiency would entail longer operational flight time for these energy-strapped applications.

1.6 Assumptions, Scope, and Delimitations

1.6.1 Assumptions

1. The nominal values for the motor parameters are based on the values presented in Table 4.1 as well as in [56].
2. The Flight Plan for the UAV will be based on [86].

1.6.2 Scope

1. The study will focus on the design of the estimator only, the remaining control blocks of the FOC are already available in the simulation library.
2. The estimator's inputs, that also correspond to the training data, are the stator voltages and stator currents.
3. The estimator's outputs are the rotor speed and position.

1.6.3 Delimitations

1. The study will be limited only to pure simulation given the current constraints at the time of the study.

2. The control scheme for the motor drive is limited to field-oriented control only.
3. The training of the neural network is limited to offline training.