



Torque modeling of Switched Reluctance Motor using LSSVM-DE

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ABSTRACT

An accurate and precised model of Switched Reluctance Motor (SRM) captures the performance of the machine. The model is highly nonlinear and complicated due to its doubly salient structure. In this paper, a nonparametric regression model for torque parameter of SRM was developed using Least Square Support Vector Machine (LSSVM) applying the concept of kernel based learning. Hyperparameters of LSSVM improves the model accuracy and generalization ability. The optimal values of hyperparameters were obtained by using Differential Evolution (DE) and high accuracy was observed. The regression model was developed using the magnetic characteristics of SRM by 2-D Finite Element Methods (FEM). The results obtained have been compared with the other optimization algorithms such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO).

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1. Introduction

Switched Reluctance Motor acts as a suitable choice for the high speed industrial drives because of its energy efficiency, wide range of speed operation, low cost, rugged construction, fault tolerant capability and good dynamic response of the drive. Due to its saliency in both stator and rotor and possibility for magnetic saturation in the stator, its characteristics are highly nonlinear and dependent on rotor position and phase current [1]. Use of torque sensor is highly essential for the measurement and control of torque in SRM drive application. However, the cost of torque sensor is more expensive and operational bandwidth is limited. Moreover, the knowledge about the values of inductance, flux and torque produced can be obtained through indirect approach. The characteristic values can be predicted through identification methods or modeling algorithms. The inductance, flux and torque characteristics of SRM can be modeled by the following methods:

1.1. Direct measurement techniques

In direct measurement technique, the value of inductance, flux and torque are measured at various rotor positions under static or dynamic condition [2,3]. As the measurement is carried out under

dynamic environment, the accuracy is high. The need of sophisticated sensors and rotor locking arrangement makes it tedious and cumbersome for the measurement.

1.2. Finite Element Methods

If the geometry of the machine is known, then the characteristic values can be easily simulated using any Finite Element Method (FEM) software [4,5]. The values of flux and torque are obtained by computing the magnetic vector potential and co-energy over the cross section of the machine using suitable numerical computation algorithm. The FEM analysis can be done using both 2-D and 3-D solvers. As the 2-D solver does not account the end effects of the machine, the accuracy is less. For accurate modeling, suitable correction factor can be included with the results obtained using 2-D solver.

1.3. Analytical modeling

In analytical modeling, the torque profile of the motor is derived from the accurate analytical flux linkage modeling of the motor. The mathematical expression is obtained using the following methods:

- (a) Based on magnetic field analysis [6].
- (b) Based on geometrical data [7].
- (c) Based on magnetic equivalent circuit [8,9].

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- (d) Using Fourier decomposition, Polynomial expression, trigonometric functions or exponential functions [10].
- (e) Compact flux linkage model using truncated Fourier series [11].
- (f) Cubic interpolation [12].

1.4. Intelligent methods

Further, intelligent approximation algorithms like Artificial Neural Network (ANN), Artificial Neuro-Fuzzy Inference System (ANFIS) and Radial Basis Function (RBF), which are well suited for modeling nonlinear systems, were used for estimating or modeling the torque profile both in online and offline modes [13–16]. They are conditioned most on the observational data obtained either by direct measurement or FEM. Due to the availability of prior knowledge about the model; generalization is possible in the intelligent systems. Regardless of its advancement, the neural network model suffers from local minima solution, possibility for overfitting and dependency on quality and quantity of data. In order to overcome the drawbacks of neural networks, Support Vector Machines (SVMs) are widely proposed and used instead of artificial neural network. Like ANNs, SVMs can be used both for classification and regression problems.

SVM is a classifier derived from statistical learning theory and was first introduced by Vapnik [17]. For regression, kernel based learning is used for learning the nonlinear function in a linear learning machine where the nonlinear data are mapped into a high dimensional feature space. The process of employing SVMs in regression problems is referred to Support Vector Regression (SVR). The SVM has the capacity to prevent the over fitting by generalization theory. LSSVM is a least square version of SVM which considers the inequalities for classical SVM. As a result, the solution of LSSVM follows directly from solving a system of linear equations instead of quadratic programming, which makes LSSVM faster than SVM with reduced computation time. LSSVM can be used for classification and regression [18]. However, the accuracy of regression model using LSSVM rely on the values of the hyperparameters used [19]. In the past, several reports are available for LSSVM based forecasting model being used in wide range of applications [20,21]. For SRM, inductance and flux characteristics were forecasted and the hyperparameters were optimized using optimization techniques such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Artificial Bee Colony (ABC) algorithm [22–24].

In 1995, Storn and Price [25] developed an efficient, parallel, direct search algorithm called Differential Evolution (DE) algorithm for optimizing real value parameters in continuous space. Being a direct search method, it is applied for nonlinear and experimental minimization problems. In spite of being an evolutionary optimization algorithm, it is different from the way the operators of evolutionary process are being applied. From the previous reports, it is observed that DE has outperformed PSO, GA and other evolutionary algorithms. The aim of LSSVM regression model is to forecast the values with minimal error. Therefore, DE is well suited for tuning the hyperparameters of LSSVM regression model. In this work, a four phase, 500 W, 8/6 SRM was considered for the study. The static characteristics of the machine were analyzed by 2-D finite element method using MagNet CAD package. In this paper, nonlinear modeling of Switched Reluctance Motor characteristics based on LSSVM-DE has been proposed. The hyperparameters of this model are selected optimally using Differential Evolution (DE). The paper is organized as follows: the mathematical model of SRM and the theory of LSSVM & Differential Evolution are given in Sections 2 and 3 respectively. In Section 4, Modeling of torque using LSSVM-DE technique was discussed. Section 5 brief about the numerical results obtained using the above technique. Application of LSSVM-DE torque model was discussed in Section 6.

2. Mathematical model of SRM

The motor is doubly salient in nature with less number of rotor poles than stator. When a rotor pole is pulled into alignment with an excited phase, a reluctance torque is produced and the current direction is unipolar. Due to double saliency and magnetic saturation, the winding inductance L_k ($k = 1-4$) varies with current i and rotor position θ . The voltage equation of each phase is given by

$$V_k = Ri_k + \frac{d\psi_k}{dt} \quad (1)$$

where V_k is the voltage applied across the phase winding, Ri_k is the voltage drop due to winding resistance and ψ_k is the total flux-linkage of the coil. The general expression for the torque produced by one phase at any given rotor position θ is

$$T_{ph} = \left(\frac{\partial W}{\partial \theta} \right)_{I=\text{const}} \quad (2)$$

where W is the co-energy. Total instantaneous torque is given by the sum of the individual phase torques.

$$T_e(\theta, I) = \sum_{i=1}^{N_{ph}} T_{ph}(\theta, I) \quad (3)$$

where N_{ph} is the number of phases in the machine. The electromagnetic dynamic model of the motor and the load are expressed as shown in Eq. (4)

$$T_e - T_l = J \frac{d^2\theta}{dt^2} + B \frac{d\theta}{dt} \quad (4)$$

where T_l is the load torque, J is the moment of inertia of rotating masses and B is the viscous friction coefficient. The load torque is a function of the angular speed, depending on the type of load.

3. Basics of LSSVM and Differential Evolution

3.1. Basics of LSSVM

Vapnik introduced the Support Vector Machine based on the Statistical Learning Theory (SLT) and the Structural Risk Minimization principle. In SVM, the solutions are obtained by solving the set of nonlinear equations using Quadratic Programming (QP), thereby avoiding the local minima. Suykens proposed a modified version of SVM known as Least Square Support Vector Machine [18] which transforms the quadratic optimization problem into a set of linear constraints. This can be specifically described as follows.

Consider the given set of training data (D)

$$D = \{ (x_k, y_k) \mid k=1, 2, \dots, N \} \quad (5)$$

where N is the number of training data pairs, $x_k \in R^n$ is the regression vector and $y_k \in R$ is the output. The regression model is formulated by a nonlinear mapping function $\varphi(\cdot)$ which maps the input data to a higher dimensional feature space.

$$y = \omega^T \varphi(x) + b \quad (6)$$

where ω and b are the weight vector and bias respectively. The LSSVM can be used as both a classifier and function estimation. When it is used for function estimation, the quadratic loss function is taken as the cost function for optimization. The standardized cost function of LSSVM is

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