The Development of Induction Motor Characteristic by Using Radial Basis Function (RBF) Learning Method for Electric Vehicle Application

Era Purwanto[1], GigihPrabowo[2], ArmanJaya[3], EndroWahjono[4], Moch. Machmud Rifaldi[5]

Politeknik Elektronika Negeri Surabaya
INDONESIA.

era@pens.ac.id

ABSTRACT

There is a growing interest in electric vehicles due to environmental concerns. Recent efforts are directed toward developing an improved propulsion system for electric vehicles applications. This paper is aimed at developing the system modeling of induction motor by using radial basis function which use in electric vehicle propulsion systems. The vehicles' dynamics are studied in an attempt to find an optimal torque-speed profile for the electric propulsion system. This study reveals that the vehicles' operational constraints, such as initial acceleration and grade, can be met with minimum power rating if the power train can be operated mostly in the constant power region. Several examples are presented to demonstrate the importance of the constant power operation. Operation of several candidate motors in the constant power region is also examined. There are difficulty to determine the control system method is suitable for the induction motor system, the characteristic of induction motor is most important information which can be used to solve this problem. The modeling of the induction motor is most important method to find that characteristic, the d-q model was developed in the last view year, in this paper the Application Of Radial Basis Function(RBF) Learning Method to find the Induction Motor modeling is proposed, this method is used to solve the nonlinear problem in induction motor model. The result was calculated by using the C language program and the error was found at 0.00001

Keywords: Electric vehicle, hybrid electric vehicle, motor drives, road vehicle electric propulsion, Radial Basis Function

INTRODUCTION

In this paper the application of RBF learning in Neural Network is used to find the induction motor model. The Characteristic of Induction motor can be found by using conventional modelling system such as d-q model. The Radial Basis Function of Neural network is used in this work as possible solution to the modeling of induction motor .

Modeling of Induction motor is coupled to complex nonlinear system may become a challenging task. However commissioning of high performance drives systems which used the induction motor is required accurate models of induction motor. Gray-Box modeling is presented in this work as a possible solution to the modeling problem of mechanical loads. In gray-box, modeling the system model is partitioned into a known and an unknown part. The known part of the model is derived from physical principles while the unknown part is modeled using a black-box model. The investigation of the use this modeling approaches to model the electrical machine-mechanical load system of an electric drive.

In this application, the electric part of the system is well understood from the corresponding governing physical laws, while the mechanical part of the system could be too complex or unknown. In this paper is present the use of neural networks as the black-box models for the mechanical part. In this work expectation is to use these models in a self-commissioning scheme, making the drive controller capable of tune its parameters for a wide range of mechanical loads. The use of this modeling approach is illustrated with a DC drive system driving an unknown static load. Simulation results are presented which study the capability of the network to approximate the load as a function of the number of layers for a fan type load and a friction load.

PROPOSED SYSTEM

In the fig.1 is shown the block diagram of induction motor with nonlinearity part, in this paper in this paper to solved that problem, the application of radial basis function learning of neural network is proposed, design detail of this system is shown in fig.2, the system is consist input layer, hidden layer and output layer.

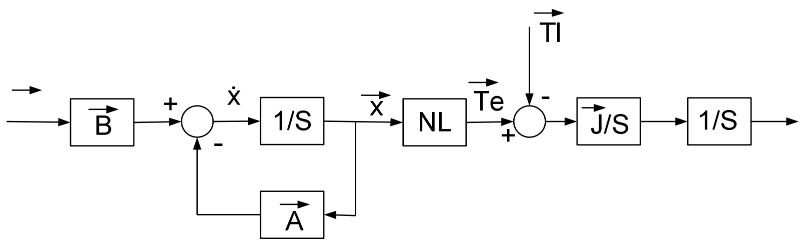

Fig 1. The Block diagram model of Induction

The input layer is consist of 4 neuron for all the current stator and rotor parameter in the d-q frame, and the out layer is consist 1 neuron for the torque electric parameter, the hidden layer is consist 9 neuron with the composition 2,3,4 neuron, this composition is tried by using try and error method to get the minimum error.

INDUCTION MOTOR MODELING

The motor induction model on the d-q model is expressed as shown on the equation 1 as below; and the equation is developed by using state space, and it can be expressed as following equation in the stationary reference frame.

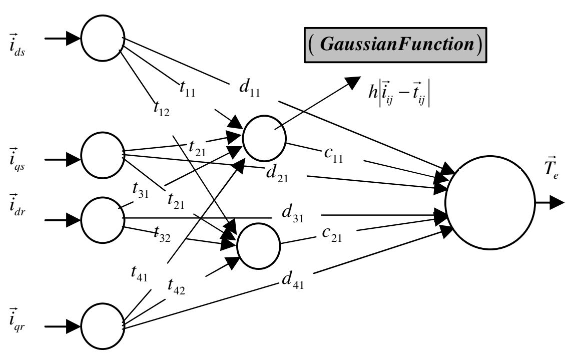

Fig 2. The structure Of Neural Network

$$\frac{d}{dt}\begin{bmatrix}\mathbf{i}_s \\ \lambda_r\end{bmatrix} = \begin{bmatrix}\mathbf{A}_{11} & \mathbf{A}_{12} \\ \mathbf{A}_{21} & \mathbf{A}_{22}\end{bmatrix}\begin{bmatrix}\mathbf{i}_s \\ \lambda_r\end{bmatrix} + \begin{bmatrix}\mathbf{B}_1 \\ 0\end{bmatrix}\mathbf{v}_s \quad (1)$$

$$= \mathbf{Ax} + \mathbf{Bv}_s$$

$$\mathbf{i}_s = \mathbf{Cx} \qquad (2)$$

Where :

$\mathbf{i}_s = [\mathbf{i}_{sd} \quad \mathbf{i}_{sq}]^T$: Stator current

$\lambda_r = [\lambda_{rd} \ \ \lambda_{rq}]^T$: Rotor flux

$\mathbf{v}_s = [v_{sd} \ \ v_{sq}]^T$: Stator voltage

$$\mathbf{A}_{11} = -\{R_s/(\sigma L_s) + (1-\sigma)/(\sigma\tau_r)\}\mathbf{I} = a_{r11}\mathbf{I}$$

$$\mathbf{A}_{12} = M/(\tau L_s L_r)\{(1/\tau_r)\mathbf{I} - \omega_r \mathbf{I}\} = a_{r12}\mathbf{I} + a_{i12}\mathbf{J}$$

$$\mathbf{A}_{21} = (M/\tau_r)\mathbf{I} = a_{r21}\mathbf{I}$$

$$\mathbf{A}_{22} = -(1/\tau_r)\mathbf{I} + \omega_r \mathbf{J} = a_{r22}\mathbf{I} + a_{i22}\mathbf{J}$$

$$\mathbf{B}_1 = 1/(\tau L_s)\mathbf{I} = b_1\mathbf{I}$$

$$\mathbf{C} = [\mathbf{I} \quad 0]$$

$$\mathbf{I} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad \mathbf{J} = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$$

R_s, R_r : Stator and rotor resistance

L_s, L_r : Stator and rotor self inductance

M : Mutual inductance

σ : Leakage coefficient, $\sigma = 1 - M^2 / L_s L_r$

τ_r : Rotor time constant, $\tau_r = L_r / R_r$

ω_r : Motor angular speed

SIMULATION RESULT

The system is developed by using 2 neuron in the hidden layer configuration and it was tested by using program and the result as shown in the fig.3 and fig.4 is graphic for simulation by using runge kutte Gill method The error is found nearly 0.00001

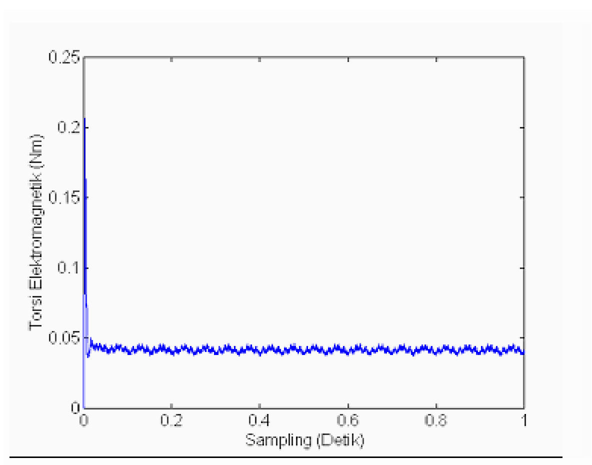

Fig.3. The Simulation model of Induction motor Using RBF on the 10.000 iteration

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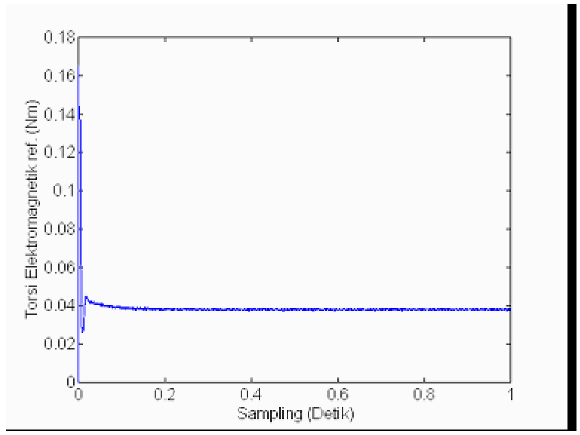

Fig.4. The Simulation model of Induction motor Using Runge Kutte Gill.

CONCLUTION

Implementation of the Radial Basis function learning Neural Network for modeling of induction motor is presented, and the result is found on the small error, thus this method can be implemented and to develop to get the characteristic of induction motor by using more better method as the for the many type machine.

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