Parameter Identification of PMSM Nonlinear Part

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Abstract— The paper describes the identification of quadrature inductances of permanent magnet synchronous motor. The identification is based on the principle of Hammerstein model.

The electrical diagram of permanent magnet synchronous motor could be divided into two parts. First one is the static nonlinearity and the second one is the linear dynamics. The identification of quadrature inductance from nonlinear part is discussed in this paper. Only inputs and outputs can be read, when the Hammerstein model is used. Since the hessian of loss function cannot be created, the calculation is divided into two parts and the variables are computed or estimated.Because only nonlinear part is used, the outputs of this part must be calculated from system outputs. The identification is carried out on the nonlinear part by Newton method.

1. INTRODUCTION

Nowadays, permanent magnet synchronous motors are widely used in many industrial applications as well as in domestic electrical appliances. These motors are developed at the same time with more efficient control. Therefore there is a growing need to know the exact parameters of motors. The more the parameters are accurate, the more effective control can be reached. There is the question: how could these parameters be identified? There are many types of identification methods. Some of them are offline methods, that are generally based on a specific input signal and subsequent evaluation of the output [1]. Other types of identification methods are online methods. These methods obtain parameter values with the motor running and working on different principles [2, 3]. One of these methods is the injecting signal to the control signal and subsequent measurement of changes in the output [4]. Or the input and output signals are evaluated (voltage, output current, and sometime speed) and the required parameters are calculated or predictively received from them [5].

Often some systems contain nonlinear part and a linear part. Depending on the order of these parts, systems can be divided into several types.The most famous systems are Wiener model [6–8] and Hammerstein model [9–11]. In Wiener model, linear dynamics is the first part and static nonlinearity is the second part.In Hammerstein model the order is reversed. In some cases the system contains more linear and nonlinear parts, and consequently the above-mentioned models are combined [12].

In our case, the aim is the identification of the permanent magnet out-runner motor inductances. The following paper describes an inductance identification based on Hammerstein model using Gauss-Newton method.

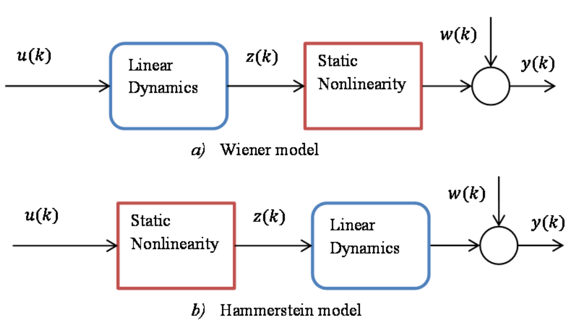

Figure 1: Wiener and Hammerstein model.

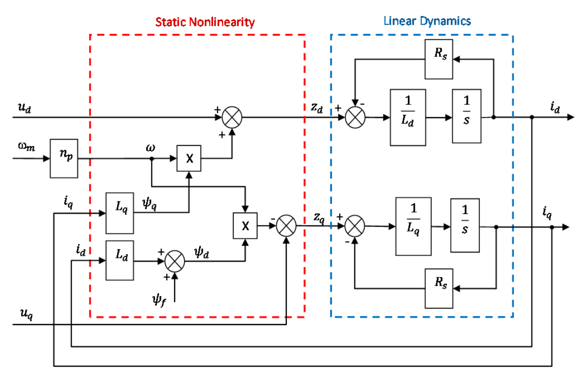

Figure 2: Wiener and Hammerstein model.

2. DISCERPTION OF THE SYSTEM

As we can see on Figure 2. the motor model can be divided into two Hammerstein models and both models include identified inductance L_d and L_d. For greater clarity, the model was divided into Hammerstein model containing variable z_d and Hammerstein model containing variable z_q. Variables are located between linear and nonlinear part of the modeland indexes of these variables are derived from the voltages that are applied to the inputs of these models.From this follows that the output of nonlinear part must be equal to the input of linear part and this equality is used for creation of loss function (Equations (4)–(5)).

Many gradient methods aresuitable for identification of nonlinear system.In our case the Newthon method is used [13].

In Newton method the direction matrix is calculated from the inverse of the Hessian H_{k-1}^{-1} of the loss function at the point θ_{k-1}.

$$\theta_k = \theta_{k-1} - H_{k-1}^{-1} J_{k-1}' f_{k-1} \tag{1}$$

where:

$$J = \begin{pmatrix} \frac{\partial f}{\partial \theta(1)} & \frac{\partial f}{\partial \theta(2)} & \cdots & \frac{\partial f}{\partial \theta(n)} \end{pmatrix}' \tag{2}$$

$$H = \begin{pmatrix} \frac{\partial J(\theta)}{\partial \theta(1)\partial \theta(1)} & \frac{\partial J(\theta)}{\partial \theta(1)\partial \theta(2)} & \cdots & \frac{\partial J(\theta)}{\partial \theta(1)\partial \theta(n)} \\ \frac{\partial J(\theta)}{\partial \theta(2)\partial \theta(1)} & \frac{\partial J(\theta)}{\partial \theta(2)\partial \theta(2)} & \cdots & \frac{\partial J(\theta)}{\partial \theta(2)\partial \theta(n)} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial J(\theta)}{\partial \theta(n)\partial \theta(1)} & \frac{\partial J(\theta)}{\partial \theta(n)\partial \theta(2)} & \cdots & \frac{\partial J(\theta)}{\partial \theta(n)\partial \theta(n)} \end{pmatrix} \tag{3}$$

Therefore, for Newton method all the second derivatives of the loss function, either analytical or estimated by finite difference techniques, must be found. In classical Newton method is the step size η_{k-1} set to 1. It is the optimum choice for the linear optimization problem, where the optimum should be achieved after one iteration.This follows directly from the second-order Taylor series expansion of loss function. But the nonlinear identification cannot be achieved in one iteration. Then the constant step size 1 can be either too small or too large relative to non-quadratic surface of the loss function. In our case it is set to 1000.

The problem of Newton method is that it reduces the value of the loss function only for positive definite Hessian H_{k-1}^{-1}. The fundamental importance of Newton method is based on the fact that the speed of convergence is of the second order if H_{k-1} is positive definite.This is the highest speed commonly occurring in a nonlinear identification. Disadvantages of Newton method are therefore connected with the second-order derivatives and the strong computing power needed for the calculation of the Hessian [13].

Loss functions are then as follows:

$$f1 = \left(-L_d i_d(k) + L_d i_d(k-1) - R_s T_{vz} i_d(k-1) + L_q T_{vz} \omega(k-1) i_q(k-1) + T_{vz} u_d(k-1)\right)^2 \tag{4}$$

$$\begin{aligned} f2 = {} & \left(-L_q i_q(k) + L_q i_q(k-1) - R_s T_{vz} i_q(k-1) - L_d T_{vz} \omega(k-1) i_d(k-1) + T_{vz} u_q(k-1) \right. \\ & \left. -\Psi_f T_{vz} \omega(k-1)\right)^2 \end{aligned} \tag{5}$$

However, the inverse matrix of Hessian cannot be created for these loss functions.Therefore loss function is modified.The modification lies in the fact that one part of system is always calculated from previous values and second part is identified (Figure 3).

In our case, only nonlinear part is identified and the linear part is calculated. Then calculated values z_d and z_q are constituted to loss function. This greatly simplifies the loss function and only one variable is then identified in each model.

$$z_d(k-1) = R_s i_d(k-1) + L_d \frac{i_d(k) - i_d(k-1)}{T_{vz}} \tag{6}$$

$$z_q(k-1) = R_s i_q(k-1) + L_q \frac{i_q(k) - i_q(k-1)}{T_{vz}} \tag{7}$$

$$f1 = \left(L_q T_{vz} \omega(k-1) i_q(k-1) + T_{vz} u_d(k-1) - z_d(k-1)\right)^2 \tag{8}$$

$$f2 = \left(-L_d T_{vz} \omega(k-1) i_d(k-1) + T_{vz} u_q(k-1) - \Psi_f T_{vz} \omega(k-1) - z_q(k-1)\right)^2 \tag{9}$$

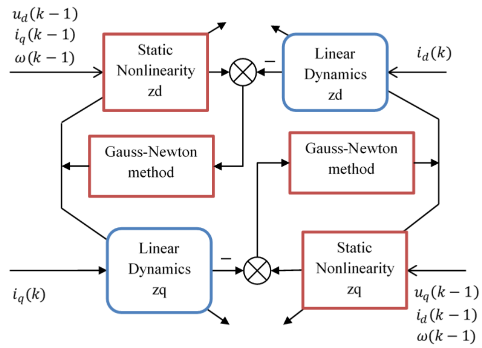

Figure 3: Wiener and Hammerstein model.

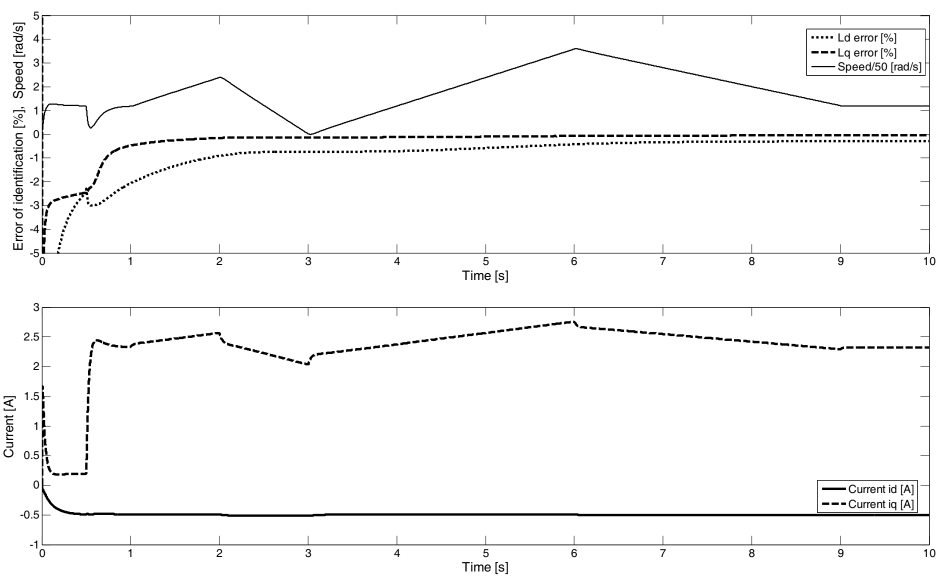

Figure 4: Error of identification.

3. CONCLUSIONS

The paper describes the permanent magnet synchronous motor as two Hammerstein models.The model contains two parts, linear dynamics and nonlinear static. The identification results from the fact that this model can be easily separated so that the output of nonlinear part is the input of linear part. Newton computational algorithm was chosen as suitable for identifying nonlinear system.After creating the loss function we found that the reverse matrix of Hessian cannot be created and the identification had to be modified. The algorithm identifies only nonlinear part and the output of this section is calculated from the output of linear part and the variables from previous identification.It is possible to identify the system with this modification. Furthermore we can greatly reduce the computational demands because Hessian is eliminated to one value.As shown in the graph chart, the method gives very good results with an error of up to 3 percent in simulations.

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