On-line Quality Control of DC Permanent Magnet Motor Using Neural Networks

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Abstract

This paper addresses the use of neural network methods to perform real-time quality control in industrial assembly lines of DC Permanent Magnet Motors (PM). This task can be viewed as a difficult non-linear inverse identification problem. Due to long parameter setting time, noisy environment and in some cases human supervision requirements, these methods are not adequate for real-time applications. Moreover, PM quality control requires the satisfaction of particular specifications rather than simple model parameter identification. So neural networks seem to be a promising paradigm.
In this study we apply fast adaptive spline networks to perform complex model inversion and reduce the effect of noise on the data. Experimental results demonstrate the effectiveness of the proposed method.

Keywords: Neural network quality control, DC motor identification, adaptive spline neural networks.

1. Introduction

On-line electrical machine quality control can be viewed as a difficult non-linear inverse problem parameter estimation in noisy environment. Electrical machine parameter estimations are well-known techniques and largely reported in electrical engineering literature.

Several papers have been published that study techniques used to estimate the parameters [1]-[6] or for fault diagnosis [10] of synchronous machines. In some of these, the estimation method consists of fixing the rotor of the PM machine in a specific position, applying a simple DC voltage source and evaluating the parameters using experimental techniques. This method is called standstill time-domain test. In [1] a method for developing a standstill dq-axis equivalent circuit model with a general number of damper windings and estimating the parameters is derived. These procedures, based on estimation theory, usually require several electrical measures and very long setting time.

These *standard* techniques are not adequate for on-line quality control. In fact, in industrial assembly lines, the diagnosis time should be as short as possible and fast non-intrusive techniques are wanted. Moreover, in motor quality control, steady-state specification estimation rather than parameter estimation is required.

The aim of this study is to develop a neural network method to estimate PM motor specifications, such as relations between torque and speed, torque and mechanical power and torque and efficiency, from a unique test in the no-load situation. A model with a given number of parameters is derived to simulate the PM machine and create synthetic input and output test data to be used during the identification process. Next some features are extracted from the test data to train a feed-forward neural network. The use of the network is essential to perform complex model inversion, reduce the effect of noise on the data and fits the mask of the industrial quality specifications.

2. Permanent Magnet Motor Model

The DC machine model used in this study is shown in fig. 1 [7][8]. Since this type of motor uses a permanent magnet to generate the magnetic field in which the armature rotates, the electrical circuit in the armature alone can model the motor. In this simple model R_a and L_a indicate the equivalent armature coil resistance and inductance respectively and v_a the voltage supplied by the power source. Kirchoff's voltage law leads to the following equation:

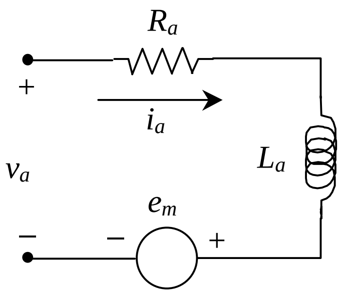

Fig. 1: PM machine armature equivalent circuit.

$$v_a = e_m + R_a i_a + L_a \frac{di_a}{dt} \tag{1}$$

where e_m is the back electromotor force. By examining the effect of the magnetic field in the motor, and realizing that magnetic flux is constant, we can arrive at the following two equations relating the torque t_m and the motor speed output ω to the supplied current and voltage:

$$e_m = K_v \omega \tag{2}$$

$$t_m = K_m i_a \tag{3}$$

The constants K_v and K_m are dependent on the particular motor, but if they are expressed in SI Units, their values are always equal.

In addition to the electrical equations, we should consider the load effect. It can be treated generally as sum of three terms: a speed independent resistant torque (t_0), a torque proportional to the speed according to a frictional coefficient (F) and a torque proportional to the speed derivative according to an inertia moment (J):

$$K_m i_a = t_0 + F_t \omega + J_t \frac{d\omega}{dt} \tag{4}$$

In (4), the symbols F_t and J_t include both load effects and the effects those are provided by the frictional losses within the motor and the rotor inertia respectively. We can rewrite the above relations in compact state space form as:

$$\frac{d}{dt}\begin{bmatrix} i_a \\ \omega \end{bmatrix} = \begin{bmatrix} -\frac{R_a}{L_a} & -\frac{K_v}{L_a} \\ \frac{K_m}{J_t} & -\frac{F_t}{J_t} \end{bmatrix} \cdot \begin{bmatrix} i_a \\ \omega \end{bmatrix} + \begin{bmatrix} \frac{1}{L_a} & 0 \\ 0 & -\frac{1}{J_t} \end{bmatrix} \cdot \begin{bmatrix} v_a \\ t_0 \end{bmatrix} \tag{5}$$

Let Σ, *t*he unknown parameter set to be estimated defined as:

$$\Sigma = [R_a, L_a, K_v, K_m, F_t, J_t\ ], \tag{6}$$

we remark that: i) not all the parameters are observable; ii) the identification task requires a specific input signal.

3. Neural Network for Parameters Estimation

3.1 Training Algorithm

The first step in identifying the permanent magnet machine using neural networks is to define the appropriate input and output vectors for the net. Since our aim is to reduce the evaluation time, we consider two phases: an off-line training process and an on-line fast estimation one. Fig. 2 illustrates the block diagram of the training procedure: a DC step voltage signal is applied to the machine for a period of time longs enough so that the system reaches the steady state. During this time, supplied current and rotational speed responses are collected as experimental data. Next, some features are extracted from them and sent to the neural network. Neural outputs, representing the parameter estimations Σ_e, are compared with the known machine parameter values Σ and the error is used to adjust the network weights.

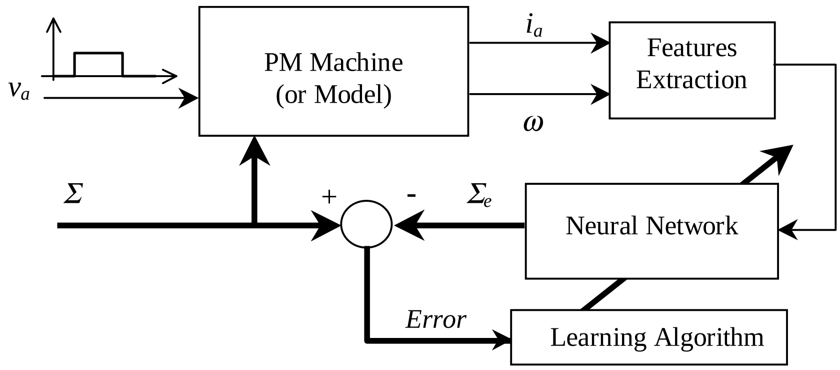

Fig. 2: Off-line neural network weights adjusting algorithm.

Once the network is trained with an appropriate training data set, it can be applied to estimate the PM machine parameters directly from the machine outputs as shown in Fig. 3. There are several advantages in using of this method: first of all the response time of the system is very short, so that it's possible to increment the diagnosis efficiency in industrial application; neural network approach, allows the estimation of the non-observable parameters Σ_e. Moreover, the neural network provides a generalization capability useful to reduce the effect of noise on the estimation process and recognize cases not occurred in the training phase.

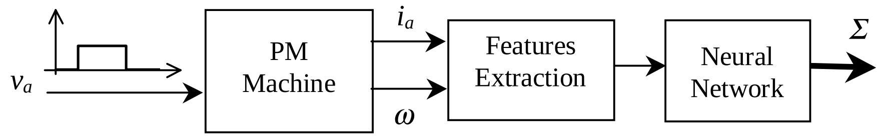

Fig. 3: On-line parameter estimation.

3.2 Training Data Set and Features Extraction

The proposed method raises two questions: how do we choose the training set and which features do we have to extract? We can answer to the first question considering the context in which we operate. Usually parameter estimation is required for diagnosis purposes; in this context we suppose each parameter varying into a restricted range, between a min and a max. We define Σ_o the set of central values of such intervals Σ_{min} and Σ_{max} the sets of minimum and maximum values respectively. Since for each parameter we consider three values, in total, for N parameters we have 3^N training patterns. This large number of patterns can be reduced considering most significant parameters only.

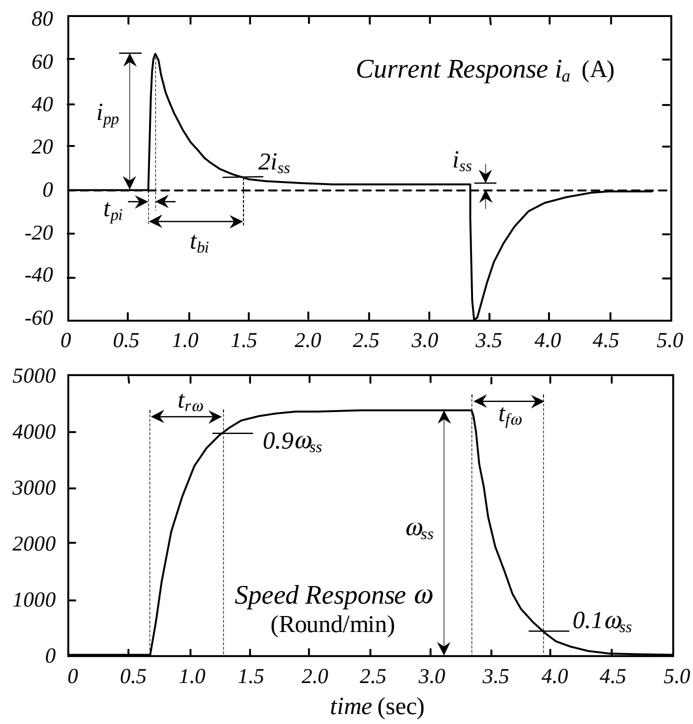

Fig. 4: Features extraction from the current and the speed responses.

As regards feature extraction, some special characteristic points of the PM model output responses are considered in Fig. 4. The number of features should be at least equal to the number of parameter to be estimated.

In our implementation, 7 features were sent to the neural network as inputs: current (i_{ss}) and speed (ω_{ss}) steady state values, current peak value (i_{pp}), speed rise time ($t_{r\omega}$) and fall time ($t_{f\omega}$), current peak time (t_{pi}) and bedding time (t_{bi}).

For an actual PM machine, before performing the feature extraction, the unwanted noise produced on the current response from the brushes (Fig. 5) should be remove using a simple low-pass filter.

As regards network structure, we have adopted a feed-forward structure with two layers. Due to their generalization capability neural network with spline activation functions is used. For more details refer to [9]-[11].

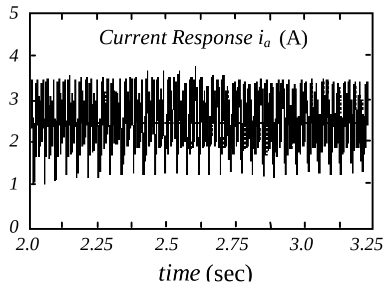

Fig. 5: Noisy current response.

4. Simulation and Results

The described procedure was first validated using simulation studies. A PM machine was simulated to create synthetic data by the model above. For each combination of parameter values, the supplied current and rotational speed responses were derived. Following the defined criteria, features extraction was executed and features were collected to create the neural network training data set.

After network training, a test data set was created in order to test the method proposed. To this purpose, parameter values belonging to the defined ranges were selected and relative responses, obtained from model, were sent to the network. Table 1 shows the estimation results for some fundamental parameters.

R_a (Ω)		K_v=K_m (V·s)		F_t (W·s^2/rad)	
Original	*estimated*	*original*	*estimated*	*original*	*Estimated*
0.120	0.112	0.0225	0.0229	$0.73 \cdot 10^{-4}$	$0.87 \cdot 10^{-4}$
0.224	0.225	0.0225	0.0224	$0.73 \cdot 10^{-4}$	$0.76 \cdot 10^{-4}$
0.120	0.113	0.0275	0.0272	$0.73 \cdot 10^{-4}$	$0.74 \cdot 10^{-4}$
0.224	0.216	0.0275	0.0270	$0.73 \cdot 10^{-4}$	$0.76 \cdot 10^{-4}$
0.120	0.110	0.0225	0.0224	$2.18 \cdot 10^{-4}$	$2.34 \cdot 10^{-4}$
0.224	0.225	0.0225	0.0229	$2.18 \cdot 10^{-4}$	$2.38 \cdot 10^{-4}$
0.120	0.119	0.0275	0.0277	$2.18 \cdot 10^{-4}$	$1.86 \cdot 10^{-4}$
0.224	0.218	0.0275	0.0274	$2.18 \cdot 10^{-4}$	$1.97 \cdot 10^{-4}$

Table. 1: Estimated parameters from simulation.

As it can be seen from the table, estimated values are in some cases quite different respect to the original values; this occurs because the system is not observable, so different parameter sets can provide identical output responses. In fact, comparing model responses from estimated parameters and from original parameters we could check their likeness also in the worst case (Fig.6).

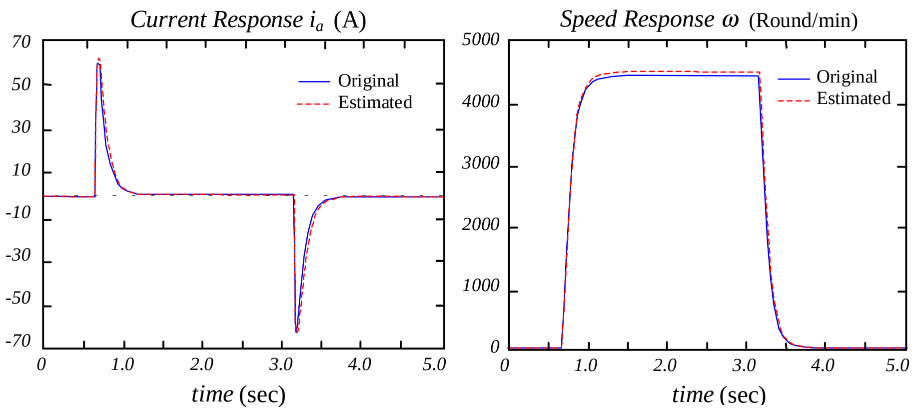

Fig. 6: Original responses and estimated responses comparison.

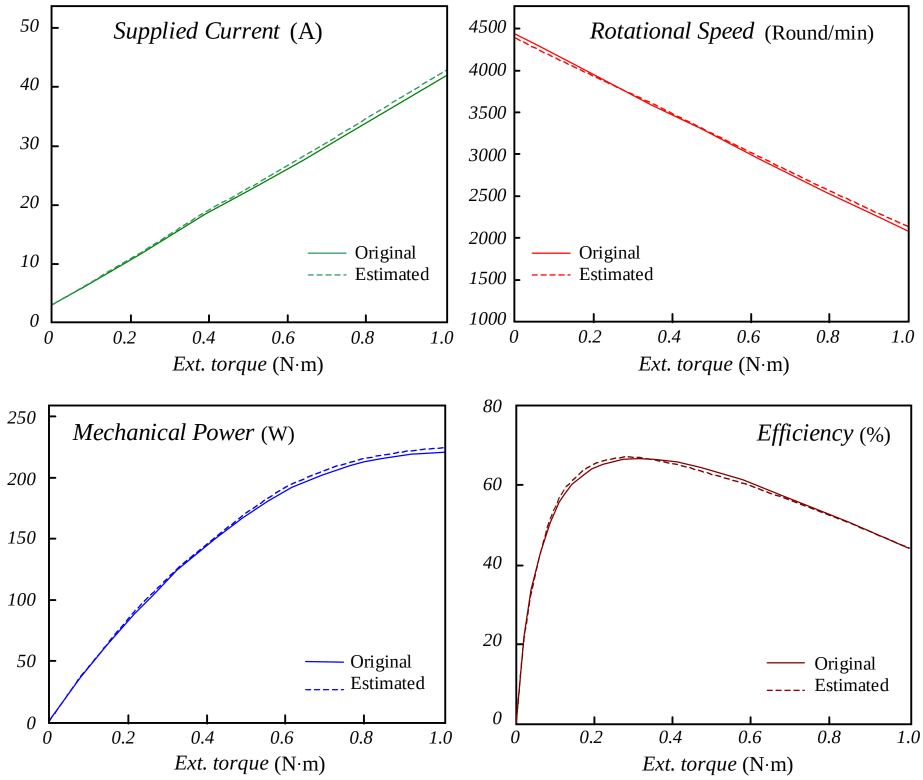

Fig. 7: Steady-state curves comparison: plots of supplied current, rotational speed, mechanical power and efficiency versus external torque.

Non-perfect parameter estimation doesn't compromise the purpose of the method. Let's consider the quality control problem; in this context we are interested basically in the steady-state motor behavior. In particular motor specifications such as relations between current, speed and mechanical power versus external torque are required. Once obtained motor parameters in the no-load situation, we can work on them to simulate other cases. Load presence affects the mechanical equation and could be treated as a contribute in frictional coefficient and in inertia moment according to the following relations:

$$F_t = F_{no-load} + F_{ext} \tag{7}$$

$$J_t = J_{no-load} + J_{ext} \tag{8}$$

Since we are interested in the steady-state condition, only the first contribute can be considered. Fig.7 shows plots of supplied current, rotational speed, mechanical power and efficiency versus external torque. All these curves are obtained from the model varying the term F_{ext}. Solid lines represent values computed by the model from original parameters, while dashed lines are the ones derived from the estimated parameters. As we can see, simulation results validate the method proposed.

5. Conclusions

The present paper focuses on the on-line permanent magnet machine quality control using neural networks. First a neural network with spline activation functions was trained with an appropriate training data set. Next, the neural model was applied for on-line parameter estimation in the no-load situation. Estimated parameters were exploited to calculate steady state values in other cases. Comparing actual specifications with those estimated we could ratify the procedure validity. The proposed method provides better performances both in terms of estimation time and noise reduction respect to standard identification ones.

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