DEEP LEARNING MODELS FOR ELECTRIC VEHICLE MOTORS: A TRANSFER LEARNING APPROACH

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Abstract

In the paper, the transfer learning technique is applied to Deep Neural Networks (DNNs) used as surrogate model for the evaluation of an Interior Permanent Magnet (IPM) motor performances. Specifically, the cogging torque is considered, with constraints on the running torque. Several ways of applying transfer learning are investigated and the results are given in terms of accuracy and reduction of computational costs.

1 Introduction

Deep learning is becoming popular in electromagnetics, for solving both direct and inverse field problems. However, several capabilities of deep learning are not exploited neither extensively investigated in literature. For the sake of an example, transfer learning is a powerful technique for re-utilizing a Neural Network (NN), previously trained on a problem or dataset, for solving a new problem or with a different dataset.

Transfer learning is particularly suitable when the database creation is very time-consuming like it happens with field problems solved by means of the Finite Element Method (FEM).

Nowadays, numerical simulations of electromagnetic devices is of paramount importance for the evaluation of the quantities like forces, torques, losses. Specifically, the evaluation of the performances of motors is more and more required, in view of new and challenging applications like electric vehicles. For instance, Interior Permanent Magnet (IPM) machines are used for high-performance application such as electric vehicles traction. In order to improve the performances of this kind of motors, many requirements can be defined. In particular, a lightweight, compact, efficient in terms of low iron losses, high running torque but low ripple torque motor are just as few design requirements. In the paper, an IPM motor, like the one studied in [1], is considered as a case study. The cogging torque is evaluated by means of a surrogate model and several transfer learning techniques are applied and investigated. The final aim is to find a surrogate model which is not too much time consuming to train and still accurate enough. Transfer learning opens the way to train a model step by step, until the desired accuracy has been achieved.

2 Case study

The Interior Permanent Magnet (IPM) motor considered as a case study is a 4-pole 24-slot brushless DC motor. The permanent magnets are made of Neodymium Iron Boron material while the rotor and stator are made of laminated steel. The outer radius is 56 mm. There are 8 coils per each of the three phases, fed by a sinusoidal current of 3 A at 50 Hz.

In order to evaluate and possibly increase the motor performance, five parameters, relevant to the rotor geometry, are considered. Specifically, they are: width d, length l and position h of the magnets, respectively, thickness b of the bridge and its orientation α, see Fig. 1.

Each parameter can vary in an admissible range as shown in Table I.

Design variable	*d [mm]*	*l [mm]*	*h [mm]*	*b [mm]*	α *[deg]*
lower upper	1 3	10 22	8 12	0.5 2	1 5

Table 1: Variation range for the motor parameters.

A parametrized 2D Finite Element (FE) model of the motor, with a sweep length in the third z-direction equal to 65 mm, has been built in Simcenter Magnet [2]. Based on the model, both running and cogging torque are calculated, considering 90 degrees of rotor rotation (torque-angle curves). A magnetic induction field map, flux lines and motor parameters are shown in Fig. 1.

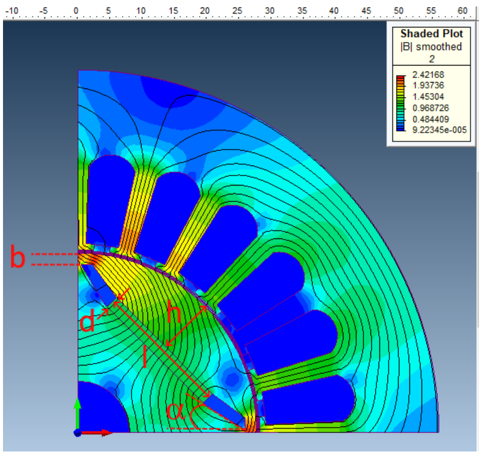

Figure 1: Magnetic induction field map and flux lines. Geometrical parameters of the IPM are highlighted.

3 DL models

In order to train the NNs that will be utilized as surrogate models for the calculation of the motor performances, a database of FE solutions has been built. Specifically, many geometries, randomly sampled in a feasible region, are evaluated by means of the FEM model. In order to obtain feasible motors from the practical viewpoint, motors characterized by a running torque lower than e.g. 0.35 Nm have been taken out from the database. For each solution, the values of both geometrical parameters and running and cogging torques are stored in the database.

Deep Neural Networks (DNNs), feed-forward and fully connected, are used for the prediction of the cogging torque. The architecture of the synthesized DNNs is described in Table 2.

Layers
1) Input (size 5×1) 2) Fully connected layer (30 neurons) 3) Sigmoid activation function 4) Fully connected layer (10 neurons) 5) Sigmoid activation function 6) Fully connected layer (1 neuron)

Table 2: DNN architecture.

The DNN is trained first with a database, namely DB1, of a given number of samples, e.g. 500 samples. The trained DNN is called DNN1. Once DNN1 is trained, transfer learning is done from DNN1 to another DNN called DNN2 with the same architecture as in Table 2. The following techniques will be investigated:

1) freezing the weights of a layer, the other layers of DNN1 are trained with a new database DB2 of e.g. 500 samples;
2) initializing the weights of DNN2 with those of DNN1 and then DNN2 is trained with the new database DB2.

Both DNNs are trained with 80% of the database used for training, i.e. 400 samples, and 20%, i.e. 100 samples, used for validation. The test set is composed of 100 samples, never used for training neither for validation.

The Mean Absolute Percentage Error MAPE

$$\mathrm{MAPE} = 100\frac{1}{N}\sum_{j=1}^{N}\frac{|\hat{Y}_{j,i}-Y_{j,i}|}{|Y_{j,i}|} \tag{1}$$

where Y is the vector of N true values calculated with FE model, and $\hat{Y}$ is the vector of N values predicted by the DNN2 is calculated for evaluating the accuracy of DNN2 predictions.

4. Results

The training of DNN1 is repeated 10 times and the MAPE error calculated for the test set is equal to 7.4% as an average over the 10 runs. In Fig. 2, true versus predicted values of the test set are plotted, with reference to one of the runs.

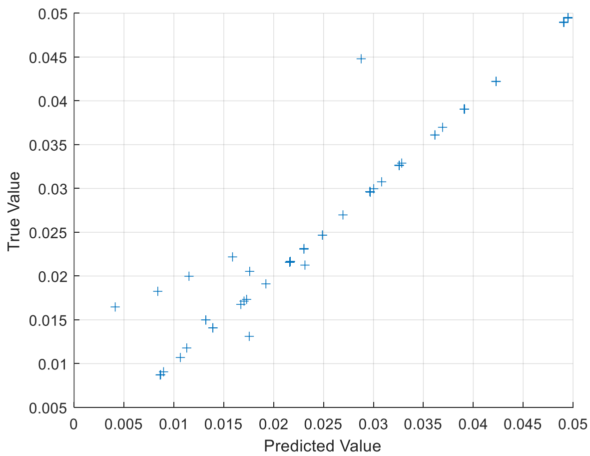

Figure 2: True versus predicted cogging torque values.

The results show that the prediction is in general accurate, because the MAPE error is acceptable. It is possible to state that there are regions in Fig. 2 where the prediction is more accurate than in others. For the sake of an example, the prediction seems to be accurate for high values of the cogging torque, but definitely less accurate for low values of the cogging torque, and this could well be a challenging aspect to deal with. It is important to be accurate in the evaluation of low values of cogging torque because these are preferable solutions from the designer viewpoint. On the other hand, however, low values of the cogging torque are usually related to low values of running torque [1], because the two performances are in contrast.

In the full work, different strategies will be applied and compared in order to highlight the best procedure of transfer learning applied to IPM motor case-study, aim to better identify the values of cogging torque in the low range.

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