Mathematical & Computational Applications, Vol. 1, No. 2, pp 87-92, 1996

MINIMUM PERMEANCE ESTIMATION OF VARIABLE RELUCTANCE MACHINES BY USING NEURAL NETWORKS

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Abstract -**A new approach was studied in this paper to calculate minimum permeance (Pmin) of variable reluctance machines (VRM). Finite element method (FEM) and neural network (NN) were employed together for estimation. The data collected by an electromagnetic finite element software (Flux 2D) were used to train NN. Trained NN was tested by another data set which are not in the training data set. Total estimation error in the test set was observed less than 2.5%. A similar study was performed with the data set collected using flux tube analysis (FTA). In this case, much larger data set was constructed by FTA since this method allows to generate larger data set. After training NN by this data set, it was tested by a test set generated by FTA. The total estimation error was observed less than 5%.**

Keywords: Variable Reluctance Machine, Artificial Neural Network, Finite element method, Minimum Permeance

1.Introduction

The variable-reluctance machine (VRM) is a doubly salient synchronous machine used as aerospace motors, generators in wind energy systems and in other applications, ranging from fractional horse power up to several hundred kilowatts. The design of machine is complicated because of its strong spatial and magnetic nonlinearities, combined with a large number of degrees of freedom [1].

One of the minor problems in the design process is the calculation of minimum permeance (Pmin). In the literature, there are two methods commonly used. These are : finite element method (FEM) and flux tube analysis (FTA). The main differences between these methods are accuracy and calculation time. Although FEM can make an accurate estimation, it takes a long time. On the other hand, the calculation time can be made shorter by using FTA, but this causes loss of accuracy. The study in this paper aims to estimate Pmin in a significantly short time period without losing too much accuracy by using FEM and neural networks (NN) together.

2.VariableReluctance Machine(VRM)

Fig.1 illustrates the rudiments of a VRM and one of its driving circuits. The diagram illustrates eight stator poles and six rotor poles. In the case illustrated there are four separate circuits or 'phases.' VRM may also be designed, depending on the application, with one, two, three, four or even more phases.

The salient poles on the stator carry concentrated windings of particularly simple form, but the salient poles of the rotor carry no windings of any kind. Both stator and rotor cores are constructed from laminated material, to reduce iron losses and for manufacturing convenience. As seen in Fig.1, diametrically opposite stator poles are excited simultaneously, and excitation of one pair of poles causes a pair of rotor poles to be attracted magnetically into alignment producing the basic torque of the device. The figure implies excitation of poles AA', and subsequently poles BB', are excited then the rotor poles bb' would move into alignment with them (with clockwise rotation). The switching sequence of the stator circuits is determined by the rotor position using some suitable transducer [2].

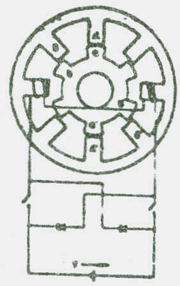

Fig.1 Elements of 4-phase VRM showing one circuit.

2.1. Definitions

1.Aligned position

When any pair of rotor poles is exactly aligned with stator poles of any phase, that phase is said to be in the aligned position.

2.Unaligned position

When the interpolar axis of the rotor(the axis exactly in the middle of two subsequent rotor poles) is aligned with the poles of any phase, this phase is called in the "unaligned position".

3.Minimum Permeance of a VRM

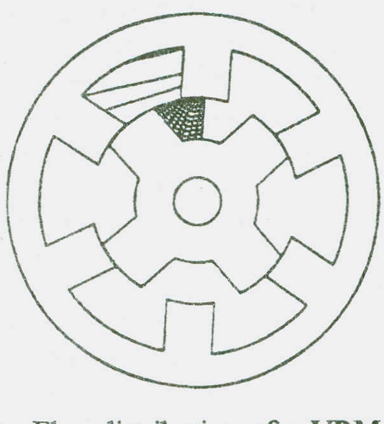

Fig.2. Flux distribution of a VRM which is in unaligned position.

Minimum permeance is the permeance of a VRM magnetic circuit where the associated rotor phase is in the unaligned position. Fig.2 depicts the unaligned position of a VRM and the distribution of flux lines in this position. Two vertical stator poles are in the unaligned position in this figure.

2.2 Dimensions Effecting Pmin

Basic machine dimensions which effect Pmin has been shown in Fig.3 There is a nonlinear relation between these dimensions and Pmin. Two approaches can be used to relate geometry and Pmin. The first one is to use dimensions directly

$$Pmin = f(\Theta r, \Theta s, Rr, Rs, Lrph, ro, rsbi)$$

The second one is to use proper ratios of dimensions as proposed in reference [5].

$$Pmin = f(k1, k2)$$

where,

$$k1 = ((2\pi/Nr) - \Theta r)Rr/(\Theta s\ Rs)$$

$$k2 = ((Lrph) / (((2\pi/Nr) - \Theta r)Rr)$$

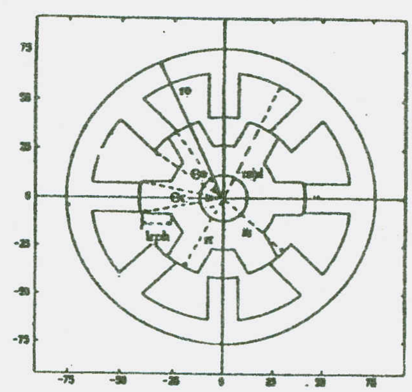

Fig. 3 Dimensions effecting Pmin

In addition to these dimensions, the length of the machine and the geometric shape of the poles are other important factors which need to be taken into consideration in some manner. In this study, since two dimensional finite element software has been used, the effect of length was not considered.

Moreover, poles are assumed in plain shape as shown in Fig.3.

2.3. Minimum Permeance Calculation Methods.

As it is mentioned earlier, the uncertainty in the flux path of the magnetic circuit makes an accurate analytical calculation very difficult. Flux tube analysis is used to calculate Pmin analytically, which gives an approximate result. A comprehensive study about this method can be found in reference [4]. On the other hand, an accurate calculation of Pmin is a very important step in the accurate calculation of motor torque and current. In order to enhance the accuracy in the calculation, finite element method (FEM) is the most commonly used numerical analysis technique. The price of the accuracy is longer calculation time than that of flux tube analysis. If this calculation is a routine task performed in a motor design process many times, the application of FEM to each different geometry is obviously not feasible. Using FEM and interpolation techniques reduce calculation time, but this reduces the accuracy as well.

3. Artificial Neural Networks

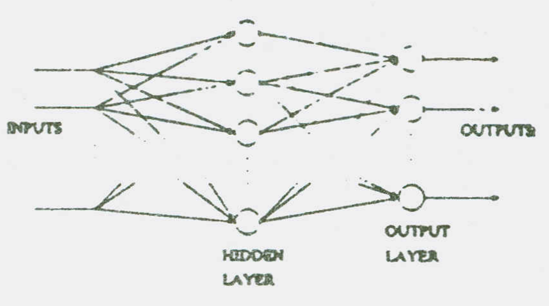

Fig.4 Topology of a 2-layer feedforward ANN.

Artificial neural networks (ANNs) are computing systems whose structures are inspired by a simplified model of the human brain. A typical 2-layer feedforward ANN is given in Fig.4. It consists of an input layer, output layer and hidden layer. Sets of nodes are arranged in these layers. Activation signals of nodes in one layer are transmitted to the next layer through links which either attenuate or amplify the signal.

3.1 Feedforward ANN structure

Representation of a H-layer ANN can be described by the following two equations.

$u_i(h+1) = \Sigma w_{ij}(h+1)\, Y_j(1) + \theta_i(h+1)$

$Y_i(h+1) = f[u_i(h+1)]$

where,

$w_{ij}(h+1)$- weight between i^{th} neuron of layer h + 1 and j^{th} neuron of layer h.

$\theta i(h+1)$- threshold to the i^{th} neuron in $(h+1)^{th}$ layer.

$u_j(h+1)$- input to the i^{th} neuron in $h+1^{th}$ layer

$Y_i(h)$- activation of i^{th} neuron in h^{th} layer

$f[.]$- sigmoid activation function $1/(1+e^{-x})$

N_h- number of neurons in the h^{th} layer

$1 \leq I \leq N_{h+1}, \quad 1 \leq j \leq N_h, \quad 0 \leq h \leq H-1$

3.2 Back-propagation learning

An ANN is trained to emulate a function by presenting it with a representative set of input/output functional patterns. The back propagation training technique adjusts the weights in all connecting links and thresholds in the nodes so that the difference between the actual output and the target output are minimized for all given training patterns. For the p^{th} training pattern (p=1,2...p), this is done by minimizing the energy function,

$E_p = (1/2)\, \Sigma_i\, (T_i - Y_i(H))^2$

with respect to all the weights and thresholds. $Y_i(H)$ corresponds to the activation function of the ith neuron in the output layer H. T_i denotes the desired target. The corresponding updates for the weights are calculated using the iterative gradient descent tecnique.

where,

$$w_{ij}^{new}(h) = w_{ij}^{old}(h)+\eta\ \partial E_p/\partial w_{ij}(h)+\nu \Delta W_{ij}(h)$$

The quantity $\partial E_p/\partial w_{ij}(h)$ is calculated by the folowing expressions.

$$\partial E_p/\partial w_{ij}(h) = \delta(h) f'[u_i(h) Y_j(h-1)]$$

$$1 \leq I \leq N_{h+1}$$

$$\delta_i(h) = \Sigma_j \delta_j (h+1) f'[u_j(h+1)] w_{ij}(h+1)$$

where $\delta_i(H) = -(T_i - Y_i(H))$

The above algorithm is commonly known as error back propagation. The constant η is the learning step while the constant ν is the momentum gain. $\Delta w_{ij}(h)$ indicates the weight change in the previous iteration. Weights are iteratively updated for all P training patterns. The training process may require many such sweeps. Suffcient learning is achieved when the total error function,

$$E_{total}=\Sigma_p E_p \quad p=1,2,3... p$$

summed over the set of all p training patterns goes below a preselected value ε. [3]

4. The proposed method for calculation of Pmin.

The main objective in this study is to reduce the calculation time significantly while increasing the accuracy as much as possible. In order to carry out this objective, FEM and NN will be employed together. Flux-2D (2 Dimensional Electromagnetic FEM package) has been used as a training data preparing tool. The accuracy of the proposed method has been tested by using the same tool.

Since FTA is an analytical way to calculate Pmin, data set generation using this method is very easy and allows us to generate much larger data set than FEM does. In order to see how this large but inaccurate data set effects generalization of NN, another data set was generated by using FTA, and then NN was trained by using these data.

5. Minimum Permeance Estimation with NN.

5.1. Data set generation.

In order to link real machine dimensions with their corresponding Pmin, reasonable machine dimensions have to be determined as a first step. After having determined reasonable machine dimensions by using criteria given in reference [4],corresponding Pmins were calculated and normalized between 0 and 1. Basically, three kinds of data set were generated. These can be summarized as follows;

1.Data Set Type. I.

Relationship of Pmin=f (k1,k2) has been used. 35 Pmin data were generated by using Flux-2D for different k1 and k2 values ranging between (1.05-2.05) and (0.125-1.0), respectively.

2.Data set Type II.

Based on the relationship of Pmin= f(k1,k2), the data were generated by using Flux tube Analysis as proposed in reference [4]. By randomly changing k1 and k2 values within the same range as above, the corresponding Pmins were calculated analytically.

3.Data set Type III

The Pmin=f(Θr, Θs, Rr, Rs, Lrph, ro, rsbi) relation was used to produce this data set. It was generated at the same time with the data set Type II. Pmin was calculated by using FTA for each random dimension.

5.2.Training and Testing of Neural Network.

Multilayer feedforward type of NN was used as a neural network. By using the backpropagation algorithm for different type of configurations and data set, the following trainings were performed. MetaNeural™ software was used for training.

5.2.1. Training and Testing for data set Type I

Data set type I consists of 35 data to use training. In order to make the most use the data available, following training method was used. 4 patterns of 35 were held out as a test file each time. Remaining 31 patterns were used to train the NN by considering overtraining possibility carefully. Whenever overtraining point was reached in terms of test file error, the training was stopped. Then 4 patterns were included to the training set, but other 4 patterns were held out as a test file. Then it was contiuned to train the NN until over training point. This process was repeated until all the patterns were used as a test pattern.

Table.1 Test Results of Trained NN by Type. I Data

pattern	target	result	error
0	0.3721	0.3595	0.0126
1	0.3282	0.2981	0.0301
2	0.2835	0.2714	0.0121
3	0.2570	0.2503	0.0067
4	0.3205	0.2924	0.0281
5	0.2666	0.2557	0.0109
6	0.3549	0.3168	0.0381
7	0.3598	0.3332	0.0266
Total	Test	Error %	2.32

The NN configuration during above process was 2-5-1. That is, 2 nodes in input layer, 5 neurons in hidden layer and 1 neuron in output layer. After training was completed, another data set was prepared for testing. This data set includes 8 patterns. The results regarding with the test file were given in Table.1

5.2.2. Training and Testing for data set Type II

Different NN configurations were experimented by using data set Type II. The results for training and testing are given in Table.2. Fig.5 illustrates how NN can generalize a 150-pattern test file.

Table.2 Test results performed by different TypeII data set

# of Trainin g patterns	# of Test patterns	Trainin g Error %	Test Error %	Config uration.
100	19	3.3	3.38	2-5-1
100	150	3.3	2.54	2-5-1
200	150	3.5	2.64	2-5-1

5.2.3. Training and Testing for data set Type III

Table.3 Test results performed by different Type III data set

# of Trainin g patterns	# of Test patterns	Trainin g Error %	Test Error %	Config uration.
200	150	2.9	3.63	7-7-1
250	30	4.13	2.23	7-7-1
200	30	4.12	2.5	7-10-1

Different NN configurations were experimented by using data set Type III. The results for training and testing are given in Table 3. Fig.6 illustrates how NN can generalize a 150-pattern test file.

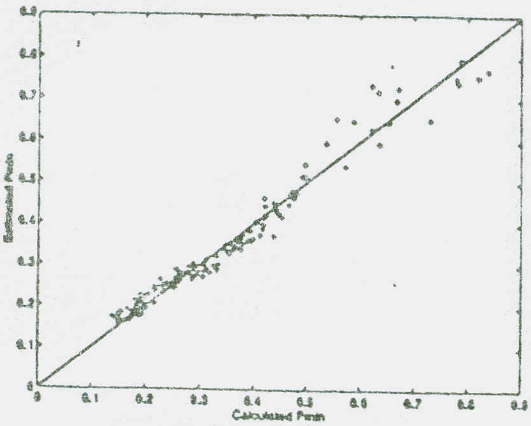

Fig.5 Error profile of NN estimation for Type II test set.

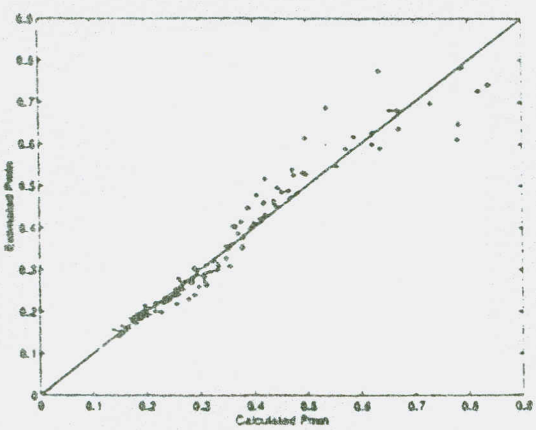

Fig.6 Error profile of NN estimation for Type III test set.

6.Conclusions

- In spite of limited amount of training data set the generalization capability of NN is fairly acceptable. The test error was less than 2.5%.
- In order to improve the estimation ability further with limited amount of data, other type of NNs and learning algorithms should be considered such as Radial Basis Function Networks, Probabilistic Neural Networks.
- Larger data set was generated by using flux tube analysis. Some experiments was performed on this data set for different NN. These experiments showed that the type of data set (Type II or TypeIII) does not effect NN generalization capability significantly.
- Estimation deficiency for large permeance values can be compansated by collecting more data around large values of permeance.

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