ANN APPROACH FOR MAGNETIC GEAR DESIGN OPTIMIZATION

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Abstract
This paper presents an artificial neural network (ANN) approach for design optimization of magnetic gear device. Proposed approach employs the ANN as an optimization problem parameters preselection. ANN is trained over a finite element method numerical magnetic model results. 3D solver based on T-*Ω formulation is used for axial magnetic gear magnetic field modeling. Radial basis function (RBF) ANNs are used in the optimization method implementation.*

Keywords: magnetic gears, optimization, artificial neural network.

INTRODUCTION

Design optimization of electromagnetic devices is a complex computational problem. Depending on used problem formulation electromagnetic design optimization can be considered as ill-posed inverse problem [1, 2]. Many electromagnetic applications could require solving of such inverse problems concerning parametric design optimization, but in complex devise structures computational complexity could limit the quality of the obtained solution [3-5].

Many engineering systems optimization tasks are causing problems for which the artificial neural networks (ANN) can be successfully applied [6,7]. Real world tasks lead to inverse problems which are in most cases ill-posed. If a standard ANN approach is applied to such inverse problems in a straightforward manner, the model will either converge approximating the target data and representing their average value, or will not converge in some cases of infinite number of output values for each input. These approaches frequently provide very poor performance, since the average of the possible solutions is not necessarily itself a solution. The ANNs could be applied as a fast unstructured algorithmic approach with low computational cost in numerical field analysis both for forward and inverse problems. At present ANNs are well developed and documented techniques for a wide range of data processing applications. [3-7]

This paper presents an artificial neural network (ANN) approach for design optimization of magnetic gear device. Proposed approach employs the ANN as an optimization problem parameters preselection. ANN is trained over a finite element method numerical magnetic model results.

AXIAL MAGNETIC GEAR

The design of the axial magnetic gear, under consideration, consists of a high-speed rotor, modulating steel segments and of a low-speed rotor. The permanent magnet pairs mounted on the high-speed rotor are 2. The modulating steel segments are 7. The permanent magnet pairs mounted on the low-speed rotor are 5. Fig. 1 shows the assembly view of the magnetic gear.

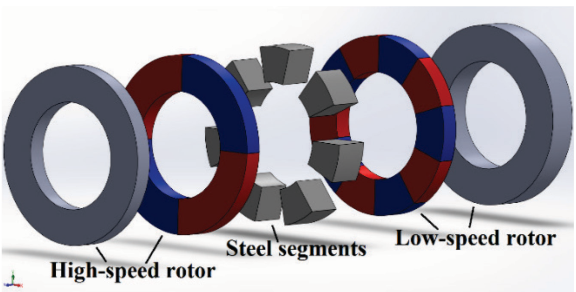

Fig. 1. *Axial magnetic gear side view.*

The sketch of the axial magnetic gear with dimensions is depicted in Fig. 2.

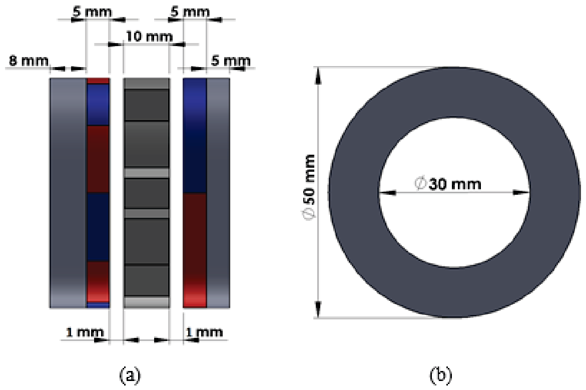

Fig. 2. *Axial magnetic gear sized drawing.*

Axial magnetic gear design materials used for the modeling are presented in Table II. The number of the design elements are shown in Table I.

TABLE I. NUMBER OF THE AXIAL MAGNETIC GEAR'S ELEMENTS AND GEAR RATIO

Symbol	Quantity	Value
p_1	high-speed rotor's permanent magnet pairs	2
p_2	number of the modulating steel segments	7
p_3	low-speed rotor's permanent magnet pairs	5
G_{13}	gear ratio	2.5

The dimensions of the elements of the axial magnetic gear are shown in Table III.

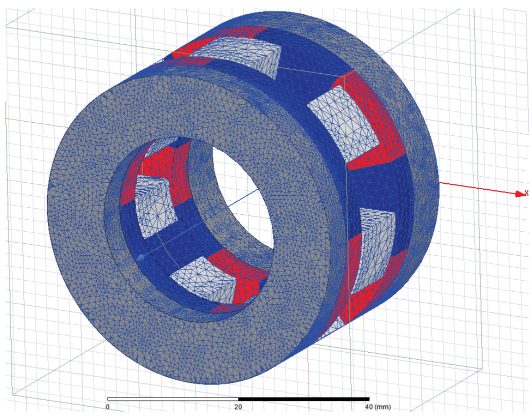

Fig. 3. *Axial magnetic gear model mesh isometric view.*

TABLE II AXIAL MAGNETIC GEAR'S MATERIALS

Material of the rotor's yokes	low carbon steel AISI 1008
Material of the permanent magnets	NdFeB35 alloy
Material of the steel segments	low carbon steel AISI 1008

The used materials of the rotor's yokes, of the permanent magnets and of the modulating steel segments are shown in Table II.

TABLE III AXIAL MAGNETIC GEAR'S ELEMENT DIMENSIONS

Symbol	Quantity	Units	Value
d	inner diameter	mm	30
D	outer diameter	mm	50
T_{HSR}	thickness of the yoke of the high-speed rotor	mm	5
T_{PM1}	thickness of the permanent magnets of the high-speed rotor	mm	5
δ_1	air gap of the high-speed rotor	mm	1
δ_3	air gap of the low-speed rotor	mm	1
T_{SS}	thickness of the modulating steel segments	mm	10
T_{LSR}	thickness of the yoke of the low-speed rotor	mm	8
T_{PM3}	thickness of the permanent magnets of the low-speed rotor	mm	5
l_{stack}	stack length of the axial magnetic gear	mm	39

AXIAL MAGNETIC GEAR MODELING

3D Ansys-Maxwell solver based on **T**-*Ω* formulation is used for axial magnetic gear magnetic field modeling. Specific formulation details on similar 3D magnetic gear design model could be found in [6]. The FEM mesh of the axial magnetic gear model is depicted in Fig.3. Surrounding free space domain is not shown. The number of the finite elements of the axial magnetic gear's parts are shown in Table IV.

TABLE IV NUMBER OF THE FINITE ELEMENTS OF THE AXIAL MAGNETIC GEAR'S PARTS

Domains	Number of the finite elements	Percentage coefficient of the number of all finite elements, %
Air	253 984	54.02
Yoke of the high-speed rotor	62 426	13.28
Yoke of the low-speed rotor	52 103	11.08
Modulating steel segments	13 946	2.97
Permanent magnets mounted on the high-speed rotor	52 448	11.16
Permanent magnets mounted on the low-speed rotor	35 251	7.50
Total	470 158	100 %

ANN FOR OPTIMIZATION

ANN Input/Output data training is a directed method which leads to changes in synaptic weights of the ANN neuron links by adopting a set of known training examples. Each example consists of a unique input signal and desired response output. The training is performed by continues ANN entrance data variation of submitted sample signal and corresponding synaptic weights changing so as to minimize the difference between the resulting output of the ANN and the desired signal. This is repeated many times for all the examples, while trained to achieve a state of ANN for a modification of synaptic weights is insignificant. This ANN is trained to match inputs to outputs. ANNs have the ability to change its synaptic weights depending on changes in the environment. This allows to be trained ANN and trained again in accordance with changes in external conditions of ANNs. The combination of the architecture of the ANN recognition with their adaptability makes them a powerful tool for the realization of adaptive classification and identification.

Accuracy of responses - in the context of the problem of recognition, ANN not only define an object belonging to a class, but also provide information on how accurate is their answer. This can be used to optimize the classification process. Integrity of information - knowledge is coded as a structure in the ANN and the activation of neurons that build them. Each neuron output weight coefficients are potentially influenced by the activation of all neurons. Therefore, global integrity of the information is a major characteristic of ANN. Error resistance - ANN have the potential to be resistant to faults. This means that if a small fraction of neurons does not work, the responses of the network will not change substantially. This effect is due to the distributed nature of logic remembered by the ANN.

Two parallel approaches are implemented here for the electromagnetic design optimization. First one is with ANN for objective function problem interpolation. Second one employs the ANN as an optimization problem parameters preselection. In both cases radial basis function (RBF) ANNs are used. In this specific optimization application, we consider single hidden layer RBF - ANN where a stochastic gradient descent optimization algorithm is used for backpropagation, and where the objective function minimization is estimated by mean-square error criterion. The output function **y** of the ANN could be defined by the following expression,

$$\mathbf{y}_{ANN}(\mathbf{x}) = \sum_{i=1}^{n} f(w_i \mathbf{x} + b_i) \qquad (1)$$

where **x** is the input data vector, w_i weight coefficients matrix vector, the b_i bias norm and n is the number of the neurons in the hidden layer.

Optimization objective function could be directly associated with $\mathbf{y} = f(\mathbf{x})$, in that case ANN is a direct interpolation of the optimization objective function that maps the search space [1-5]. That approach suffers from many disadvantages in many design parameters and multiobjective optimization. Benefits are not so significant due to complex trading and large data sets needed for that purpose. Here to train the ANN in that particular magnetic gear example was tested and trained over a FEM numerical model, where at the end the model is finally bypassed the trained ANN. First design optimization approach block scheme is demonstrated in Fig.4(a).

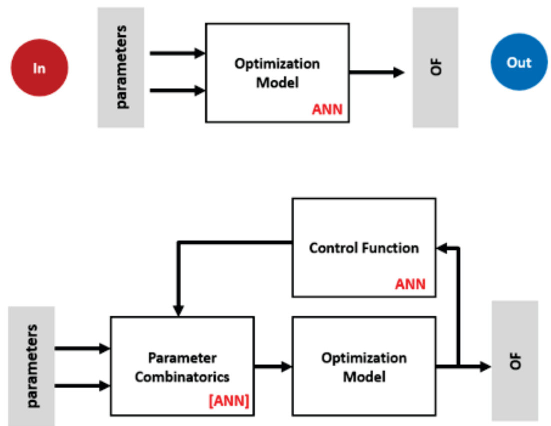

Fig. 4. ANN for objective function interpolation (a) and optimization process control and parameters preselection (b).

Second implemented design optimization approach employs the ANN as an optimization problem control and parameters preselection. Optimization control approach block scheme is shown in Fig.4(b). ANN is trained over optimization parameters control during the ongoing optimization process. Gradient descent directed method data has been provided and used for ANN training, combinations of input design parameters are selected by the ANN and gradient reposition steep is also controlled by the ANN.

We consider RBF - ANN with one internal hidden layer with 5 neurons, in the first layer we have one input (gradient of objective function) and three outputs at the third layer for the predicted values of: magnetic gear diameters, axial lengths and air-gaps. Preselected predicted values are then used and confirmed in the 3D FEM optimization model, as it is shown in Fig.4(b).

ANN is implemented via a Matlab NNet toolbox.

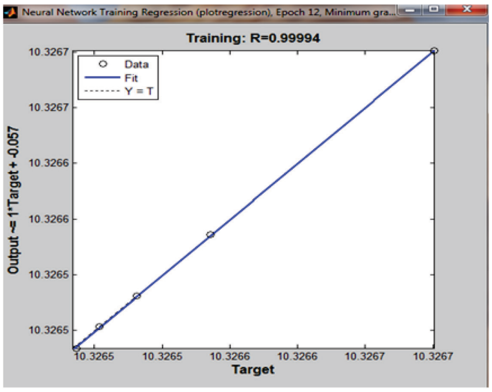

Fig. 5. *ANN fit regression linearity.*

Magnetic model data fit after the trading is presented in Fig.5. Fig.6 and Fig.7, are representing the ANN training iterative results in 12 sequential epochs.

DISCUSSION

The two implemented here approaches are tested on axial magnetic gear design optimization problem.

First one is with ANN for objective function problem interpolation. Second one employs the ANN as an optimization problem parameters preselection. In both cases RBF - ANNs are used. In this specific optimization application, we consider one hidden layer RBF – ANN. Second one implemented design optimization approach employs the ANN as an optimization problem control and parameters preselection. ANN is trained over optimization parameters control during the ongoing optimization process. Gradient descent directed method data has been provided and used for ANN training, combinations of input design parameters are selected by the ANN and gradient reposition steep is also controlled by the ANN.

In first case under investigation the ANN is a direct interpolation of the optimization objective function that maps the search space. That approach suffers from many disadvantages in many design parameters and multiobjective optimization. Benefits are not so significant due to complex training and large data sets needed for that purpose. Here we consider three parameters convex problem with ANN with one internal hidden layer with 5 neurons, in the first layer we have three inputs (magnetic gear diameters, axial lengths and air-gaps) and one output at the third layer for the objective function. Estimated ANN residual RMS error after the dataset training is estimated below 10^{-9}. Outside the training dataset but within constrain limits RMS drops to 10^{-2}. Larger problems will need exponentially increasing sizes of ANNs, so this direct interpolation approach looks tapped for a direct inversion. But in future stochastic ANNs could bring light in the computational bottleneck for larger inverse problems. Also interesting direction is the complete bypass of the computational field problems and coupled field problems [5,6], where ANN interpolation theoretically must provide strong benefits, especially in cases with time-dependent problems with repeating global matrices and non-linarites with double skews. Not least such ANN interpolations approaches have a huge potential in the emerging field of 3D visualization and virtual reality where the real time processing and algorithm speed of reaction has an advantage over the accuracy.

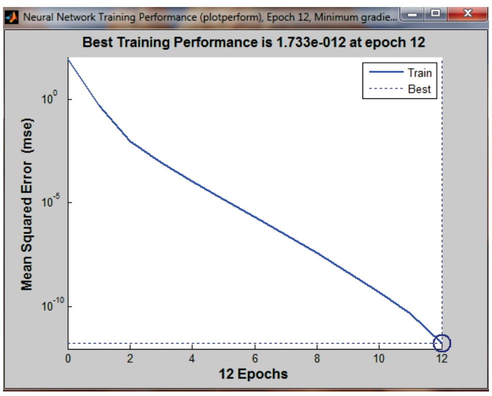

Fig. 6. *Mean square error during training epochs.*

However, in the seconds investigated optimization approach the considered ANN is again with one internal hidden layer with 5 neurons, in the first layer we have one input (gradient of objective function) and three outputs at the third layer for the predicted values of magnetic gear design parameters. In that case the control function of the ANN is not limited by the number of optimization parameters. Even a small ANN could control a huge multi-parametric optimization models if trained properly. Such ANNs schemes could mimic stochastic search algorithms as evolutionary genetic algorithms, multi-agent particle swarms, etc. ANNs will just mimic effectively the stochastic search algorithm, which means that search process is iterative and the gain will come from the reduced number of iterations from better adaptive control strategy.

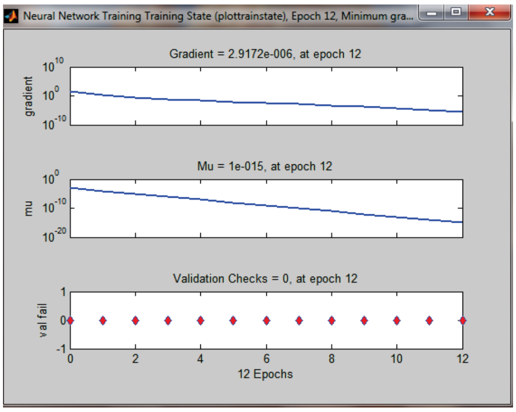

Fig. 7. ANN training iterative results.

CONCLUSION

Magnetic gear optimization approach by a ANN controlled model has been presented. Two parallel approaches are implemented. First one is with radial basis function ANN used for objective function problem interpolation. Second one employs the ANN as an optimization problem parameters preselection. ANN interpolation model that employs, in a natural and effective way, an inversion algorithm providing a solution of the electromagnetic device design problem. Further development of this optimization model can propose an efficient general solution to the electromagnetic device design problem from the same complexity class. The interpolation ANN model and optimization ANN control are both applied to the magnetic gear design. The results obtained shows the effectiveness of the proposed optimization method with ANN.

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