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EVOLUTIONARY BASED OPTIMAL DESIGN OF SR MOTORS VIA NEUROFUZZY MODELING OF NATURAL FREQUENCIES OF CYLINDRICAL SHELLS

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Abstract. Analysis of dynamic behavior of cylindrical shells is essential in design wherever it is used. Equations of shell vibrations are partial differential equations of order eight which their exact solution is possible only in special cases with a few known boundary conditions and with a lot of simplified assumptions. On the other hand finite element method does not yield a lumped model or a general solution for natural frequencies of cylindrical shells. In this paper natural frequencies of cylindrical shells in a wide range of dimensions are obtained with either exact solution or finite element method and they are applied to training of a Locally Linear Neurofuzzy Network. Finally a general model for calculation of natural frequencies of cylindrical shells has been proposed**.** Then the model has been applied for optimal design of a Switched Reluctance motor with the evolutionary algorithms as optimization method.

1. Introduction

Evaluation of structure vibrations is of great concern in mechanical design. In this approach, calculation of their natural frequencies is the first step. Because they play a great role in dynamic behavior of structure in the case of forced vibrations. In addition, in order to avoid breaking down as a result of resonance, calculation of the structure natural frequencies is essential. Furthermore, many structures such as vessels, pipes, rackets, electrical motors and generators, turbo machineries, flues etc. can be modeled as cylindrical shells. Therefore, calculation of natural frequencies of cylindrical shells has attracted much attention of designers. On the other hand exact analytical solution of this problem is not available except in a few known boundary conditions and by a lot of simplified assumptions like ignoring the influence of shear forces and rotational inertia as well as being thin-walled and long for the shell. Therefore, a lumped model in a wide range of dimensions was never found. Many works have been done in order to solve dynamic behavior of cylindrical shells and find natural frequencies of them. In [1] a closed form solution is obtained for this purpose for a few boundary conditions. Experimental methods as well as analytical approaches are applied to sound transmission analysis of cylindrical shells. In [3] an approximate frequency formula is proposed for piezoelectric circular cylindrical shells. In [4] effects of rotating on vibrations of cylindrical shells are probed. Fluid filled cylindrical shells are used widely in vessels and pipes modeling. Their vibration is solved in [5-7].Also, in [8, 9] the dynamic behavior of anisotropic and composite shells is solved.

In this paper, the aforementioned problem is going to be solved by means of a Locally Linear Neuro Fuzzy Model which will be trained by some results obtained from either finite element method or exact solutions depending on the dimensions of the annular cylinder. Comparison between target and network output shows acceptable errors in fitness. The proposed model has been applied to optimal design of a switched reluctance motor by means of the evolutionary algorithms which are optimization and search procedures motivated by genetics and the process of natural selection.

In section 2 vibrations of cylindrical shells is described. Section 3 is dedicated to description of Locally Linear Neuro Fuzzy Models as a great approach to nonlinear modeling. This approach is applied to Modeling of natural frequencies of cylindrical shells in section 4. In section 5 the results of modeling are evaluated. In section 6 Vibrations of Switched Reluctance (SR) motors are introduced and finally an evolutionary algorithm is applied in section 7 to optimization of stator geometries of SR motors in order to reduce their vibrations and acoustic noises.

2. Vibrations of cylindrical shells

Vibrations of cylindrical shells can be divided into three parts: Axial vibrations, circumferential vibrations and torsional vibrations. General differential equations for dynamic behavior of cylindrical shells with the radius of ***R*** and the thickness of ***h*** and the density of ρ are as below (Fig. 1) displacement in axial, radial and circumferential directions are shown *by* u_x, u_z & u_θ, respectively.

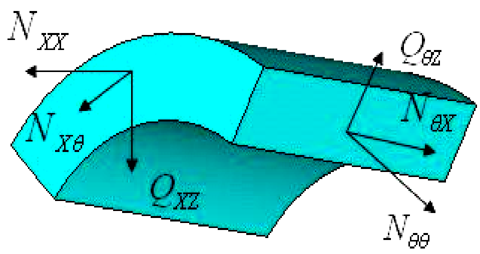

Fig. 1- Force distribution on the cylindrical shell element

$$\frac{\partial N_{xx}}{\partial x}+\frac{1}{R}\frac{\partial N_{\theta x}}{\partial \theta}+q_x=\rho h\frac{\partial^2 u_x}{\partial t^2} \quad (1)$$

$$\frac{\partial N_{x\theta}}{\partial x}+\frac{1}{R}\frac{\partial N_{\theta\theta}}{\partial \theta}+\frac{Q_{\theta z}}{R}+q_\theta=\rho h\frac{\partial^2 u_\theta}{\partial t^2} \quad (2)$$

$$\frac{\partial N_{xz}}{\partial x}+\frac{1}{R}\frac{\partial N_{\theta z}}{\partial \theta}-\frac{N_{\theta\theta}}{R}+q_x=\rho h\frac{\partial^2 u_x}{\partial t^2} \quad (3)$$

$$Q_{xz}=\frac{\partial M_{xx}}{\partial x}+\frac{1}{R}\frac{\partial M_{\theta x}}{\partial \theta} \quad (4)$$

$$Q_{\theta z}=\frac{\partial M_{x\theta}}{\partial x}+\frac{1}{R}\frac{\partial M_{\theta\theta}}{\partial \theta} \quad (5)$$

in which ***M*** is the bending moments per length, ***N*** is axial and circumferential forces per length and ***Q*** is shear forces per length. However, influences of shear forces and rotational inertia are ignored [10, 11]. By substitution stress-strain relations and deformation-strain relations into Eqs. (1-5), some new relations will be obtained:

$$L_x(u_x,u_\theta,u_z)+q_x=\rho h\frac{\partial^2 u_x}{\partial t^2} \quad (6)$$

$$L_\theta(u_x,u_\theta,u_z)+q_\theta=\rho h\frac{\partial^2 u_\theta}{\partial t^2} \quad (7)$$

$$L_z(u_x,u_\theta,u_z)+q_z=\rho h\frac{\partial^2 u_z}{\partial t^2} \quad (8)$$

in which **L** is a partial differential operator .Donnell [10] has shown that Eqs.(6-8) with some assumptions such as being thin-walled can be simplified to:

$$\frac{\partial^2 u_x}{\partial x^2}+\frac{1-\nu}{2R^2}\frac{\partial^2 u_x}{\partial \theta^2}+\frac{1+\nu}{2R}\frac{\partial^2 u_\theta}{\partial x \partial \theta}+ \frac{\nu}{R}\frac{\partial u_z}{\partial x}-\frac{1-\nu^2}{E}\rho\frac{\partial^2 u_x}{\partial t^2}=0 \quad (9)$$

$$\frac{1+\nu}{2R}\frac{\partial^2 u_x}{\partial x \partial \theta}+\frac{1-\nu}{2}\frac{\partial^2 u_\theta}{\partial x^2}+\frac{1}{R^2}\frac{\partial^2 u_\theta}{\partial \theta^2}+ \frac{1}{R^2}\frac{\partial u_z}{\partial \theta}-\frac{1-\nu^2}{E}\rho\frac{\partial^2 u_z}{\partial t^2}=0 \quad (10)$$

$$\frac{\nu}{R}\frac{\partial u_x}{\partial x}+\frac{1}{R^2}\frac{\partial u_\theta}{\partial \theta}+\frac{u_z}{R^2}+\frac{h^2}{12}\nabla^4 u_z +\frac{1-\nu^2}{E}\rho\frac{\partial^2 u_z}{\partial t^2}=0 \quad (11)$$

Solution of Eqs. (9-11) in the case of simply supported boundary conditions are as follows:

$$u_x = A\cos\frac{m\pi x}{L}\cos n(\theta-\phi)e^{i\omega t} \quad (12)$$

$$u_\theta = B\sin\frac{m\pi x}{L}\sin n(\theta-\phi)e^{i\omega t} \quad (13)$$

$$u_z = C\sin\frac{m\pi x}{L}\cos n(\theta-\phi)e^{i\omega t} \quad (14)$$

in which ***m*** is the number of axial modes and ***n*** is the number of circumferential modes (Fig.2,3)

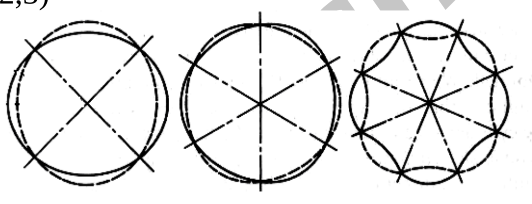

Fig. 2- Second, third and fourth circumferential modes in cylindrical shells

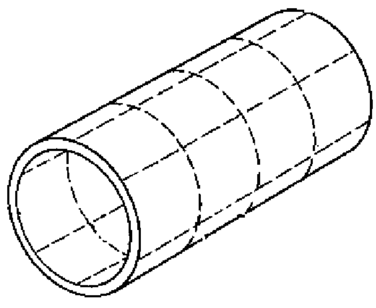

Fig. 3-Third circumferential and fourth axial node in cylindrical shells

Previous equations might be converted into a set of Ordinary Differential Equations by means of separations of variables. The determinant of ODEs coefficients leads to a characteristic equation which roots are natural frequencies. This exact solution might be obtain only by some simplified assumptions such as being long and thin-walled with a few known boundary conditions and ignoring the influences of shear forces and rotational inertia. Therefore, universal closed form solutions by means of analytical tools are not available for natural frequencies

3. Locally linear model tree identification of nonlinear systems

Neural networks have been useful mathematical tools for identification and estimation of nonlinear functions [12]. It is proved mathematically that some of neural networks and fuzzy models are General Function Approximators [12]. Especially Locally Linear Neurofuzzy Models can identify complicated nonlinear functions very rapidly and precisely. In this kind of neurofuzzy networks each neuron consists of locally linear model and an associated validity function.

In the following, the modeling of nonlinear dynamic processes using LOLIMOT algorithm is described. The network structure of a local linear neurofuzzy model [13] is depicted in Fig. 4. Each neuron realizes a local linear model (LLM) and an associated validity function that determines the region of validity of the LLM. The validity functions form a partition of unity, i.e., they are normalized such that

$$\sum_{i=1}^{M}\varphi_i(\underline{z})=1 \quad (15)$$

for any model input $\underline{z}$. The output of the model is calculated as

$$\hat{y}=\sum_{i=1}^{M}(w_{i,o}+w_{i,1}x_1+\ldots+w_{i,n_x}x_{n_x})\varphi_i(\underline{z}) \quad (16)$$

where the local linear models depend on $\underline{x}=[x_1,\ldots,x_{n_x}]^T$ and the validity functions depend on

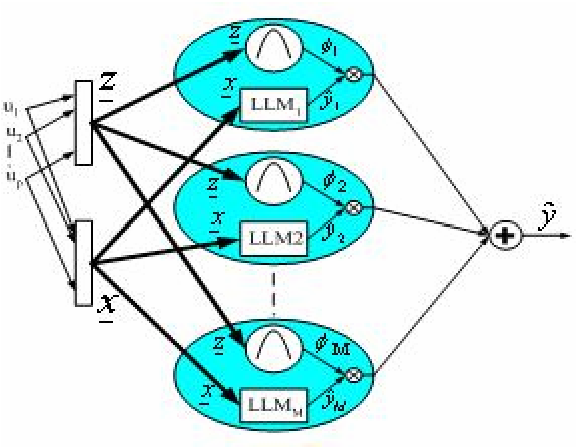

Fig. 4- Network structure of a local linear neurofuzzy model with M neurons for n_x LLM inputs x and n_z validity function inputs z.

$\underline{z} = [z_1, ..., z_{n_z}]^T$. Thus, the network output is calculated as a weighted sum of the outputs of the local linear models where the φ_i are interpreted as the operating point dependent weighting factors. The network interpolates between different Locally Linear Models (LLMs) with the validity functions. The weights w_{ij} are *linear* network parameters. The validity functions are typically chosen as normalized Gaussians. If these Gaussians are furthermore axis- orthogonal the validity functions are

$$\varphi_i(\underline{z}) = \frac{\mu_i(\underline{z})}{\sum_{j=1}^{M} \mu_j(\underline{z})} \quad (17)$$

with

$$\mu_i(\underline{z}) = \exp(-\frac{1}{2}(\frac{(z_1 - c_{i,1})^2}{\sigma_{i,1}^2} + ... + \frac{(z_{n_z} - c_{i,n_z})^2}{\sigma_{i,n_z}^2})) \quad (18)$$

The centers and standard deviations are *nonlinear* network parameters. In the fuzzy system interpretation each neuron represents one rule. The validity functions represent the rule premise and the LLMs represent the rule consequents. One-dimensional Gaussian membership functions

$$\mu_{i,j}(z_j) = \exp(-\frac{1}{2}(\frac{(z_j - c_{i,j})^2}{\sigma_{i,j}^2})) \quad (19)$$

can be combined by a t-norm (conjunction) realized with the product operator to form the multidimensional membership functions in (17). One of the major strengths of local linear neuro-fuzzy models is that premises and consequents do not have to depend on identical variables, i.e. $\underline{z}$ and $\underline{x}$ can be chosen independently.

The LOLIMOT algorithm consists of an outer loop in which the rule premise structure is determined and a nested inner loop in which the rule consequent parameters are optimized by local estimation.

1. *Start with an initial model:* Construct the validity functions for the initially given input space partitioning and estimate the LLM parameters by the local weighted least squares algorithm. Set M to the initial number of LLMs. If no input space partitioning is available a-priori then set $M = 1$ and start with a single LLM which in fact is a global linear model since its validity function covers the whole input space with $\varphi_i(\underline{z}) = 1$.

2. *Find worst LLM:* Calculate a local loss function for each of the $i=1,\dots,M$ LLMs. The local loss functions can be computed by weighting the squared model errors with the degree of validity of the corresponding local model. Find the worst performing LLM.

3. *Check all divisions:* The LLM l is considered for further refinement. The hyper-rectangle of this LLM is split into two halves with an axis-orthogonal split. Divisions in each dimension are tried. For each division $\dim = 1, ..., n_z$ the following steps are carried out:

(a) Construction of the multi-dimensional MSEs for both hyper-rectangles.

(b) Construction of all validity functions.

(c) Local estimation of the rule consequent parameters for both newly generated LLMs.

(d) Calculation of the loss function for the current overall model.

4. *Find best division:* The best of the n_z alternatives checked in Step 3 is selected. The validity functions constructed in Step 3(a) and the LLMs optimized in Step 3(c) are adopted for the model. The number of LLMs is incremented $M \to M + 1$.

5. *Test for convergence:* If the termination criterion is met then stop, else go to Step 2.

For the termination criterion various options exist, e.g., a maximal model complexity, that is a maximal number of LLMs, statistical validation tests, or information criteria. Note that the *effective* number of parameters must be inserted in these termination criteria.

Fig. 5 illustrates the operation of the LOLIMOT algorithm in the first four iterations for a two-dimensional input space and clarifies the reason for the term ”tree” in the acronym LOLIMOT. Especially two

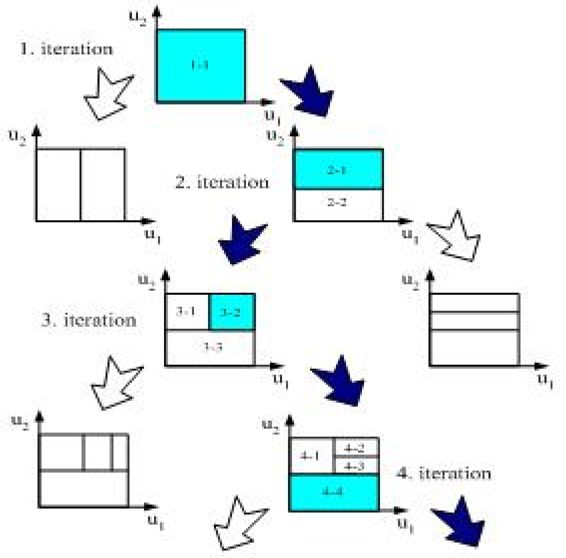

Fig. 5- Operation of the LOLIMOT structure search algorithm in the first four iterations for a two-dimensional input space (p = 2).

4. Modeling of natural frequencies of cylindrical shells using neurofuzzy network

Natural frequencies of cylindrical shells in the case of combined axial and circumferential vibrations are as follows [11]:

$$f = k\frac{c}{R} \;\&\; c = \sqrt{\frac{E}{\rho}} \tag{20}$$

where $\boldsymbol{k}$ is a nonlinear function of dimensionless geometrical parameters n, $\frac{L}{mR}$, $\frac{R}{h}$ [11].Therefore:

$$f = \sqrt{\frac{E}{\rho R^2}}\,k\left(\frac{R}{h}, \frac{L}{mR}, n\right) \tag{21}$$

In order to find a lumped model for natural frequencies one can estimate k as a function of $n, \frac{L}{mR}, \frac{R}{h}$. Thus, some values of $\boldsymbol{k}$ should be obtained from several random values of $n, \frac{L}{mR}, \frac{R}{h}$ as necessary input-output data in order to train the network as well as validity test of this training. Some of these values can be obtained from exact solution in thin-walled shells and others, specially where $\frac{L}{mR}$, $\frac{R}{h}$ was not large enough have to be obtained from Finite Element Analysis.(Figure 6) Here natural frequencies in a lot of cases are calculated by means of Finite Element Analysis with the assumption of simply supported constraint where exact solution in analytical method is not accurate. Then some of these data can be used in training of the neurofuzzy network and the others in validation of this training. The best number of neurons and the best values for network weights and other parameters are those which cause minimum error of validation data.

features make LOLIMOT extremely fast. First, at each iteration not all possible LLMs are considered for division. Rather, Step 2 selects only the worst LLM whose division most likely yields the highest performance gain. For example, in iteration 3 in Fig. 5 only LLM 3-2 is considered for further refinement. All other LLMs are kept fixed. Second, in Step 3 the local estimation approach allows to estimate only the parameters of those two LLMs which are newly generated by the division. For example, when in iteration 3 in Fig. 5 the LLM 3-2 is divided into LLM 4-2 and 4-3 the LLMs 3-1 and 3-3 can be directly passed to the LLMs 4-1 and 4-3 in the next iteration without any estimation.

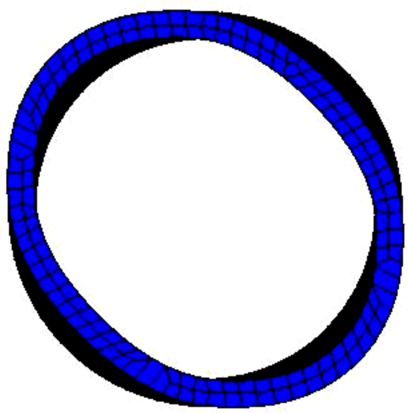

Fig. 6 – Finite Element Analysis of mode shape: m=1, n=2 in a cylindrical shell

5. Simulation results

First the network was trained by some data in the range of $1 \le n \le 20$, $0.6 \le \frac{L}{mR} \le 20$, $5 \le \frac{R}{h} \le 5000$ obtained in both ways of Analytical and Finite Element Method for different values of dimensions. In order to find a structure for the function ***k***, it can be compared with a well- known structure such as natural frequencies of beams which consists of power product of dimensions. So one can guess that $k = fR\sqrt{\frac{\rho}{E}}$ is a function as power production of n, $\frac{L}{mR}$, $\frac{R}{h}$. On the other hand, the structure of network is based on locally linear models. Thus, if the structure of the function which is going to be identified is closer to a linear structure, identification will be expected to be more accurate and it will need fewer neurons. Therefore, once the network is trained using the primary data and then it is trained using the logarithms of the same data. In Figure (7,8) it is shown that the error in the second training is much less than the first one and with the second strategy the identification is done successfully using fewer neurons than the first one. These results confirm the primary guess on the structure of function ***k***. Then the optimal numbers of neurons can be determined by training the network using logarithms of data as training data. The optimal number of neurons is that the estimation error of validation data is minimum. According to Figure (8), optimal number of neurons is M=30. Figures (9,10) show a comparison between outputs of network and target obtained by Finite Element and Analytical Methods as training and testing data. According to previous results, the errors of network on testing data are negligible and the operation of network is desirable. Figure (11) shows ***k*** as a function of $\frac{L}{mR}$, $\frac{R}{nh}$ .In this graph numerical results are available only at a few points of graph where the neurofuzzy network could estimate a precise function for ***k*** in the other points and this estimation is very close to Finite Element results.

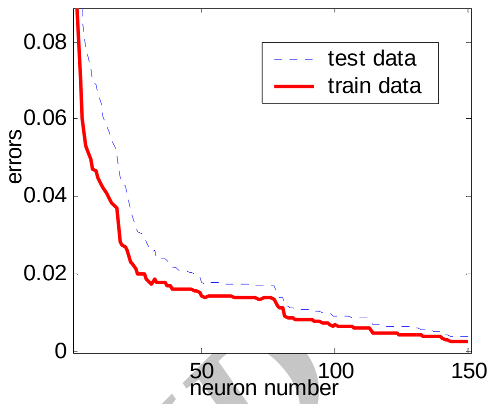

Fig. 7-Identification normalized error on training and testing data

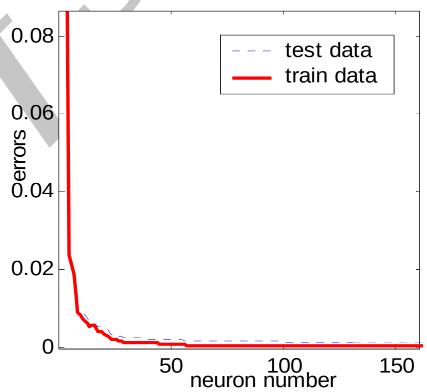

Fig. 8-Identification normalized error on the logarithms of training and testing data

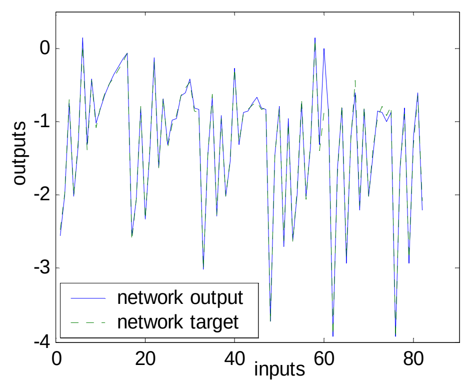

Fig. 9- Fitness of network output and the logarithm of coefficient (k) in testing data

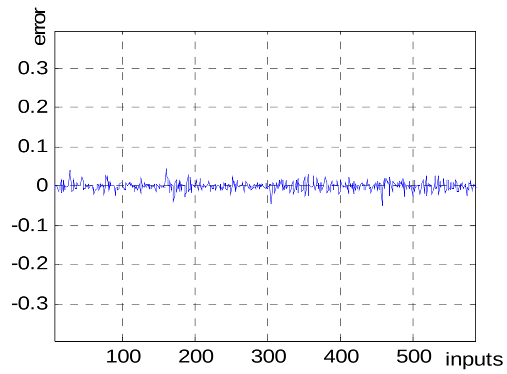

Fig. 10-Fitness error of network output and the logarithm of coefficient (k) in some training data

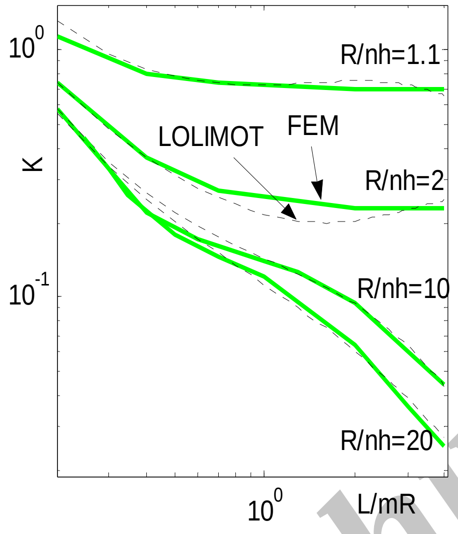

Fig. 11 - The coefficient (k) obtained from FEM analytical methods and coefficient (k) obtained from output of the Locally Linear Neurofuzzy Model versus dimensions and mode numbers

6. Optimal design of switched reluctance motor

Among all different kinds of electric motors, Switched Reluctance Motors (SRMs) have found many applications because of their special advantages such as their simple and rugged construction, hazard-free operation and their very low cost [14-18]. According to Fig. 12 in these motors, the rotor doesn't have any permanent magnet or windings in contrary with other motors [15]. The acoustic noise produced by stator vibrations in switched reluctance motors (SRMs) is a serious disadvantage for industrial applications. It is widely accepted that the radial force acting on the stator of the motor is the dominant source of vibration and acoustic noise in a well-manufactured SRM [16]. The intensity of acoustic noise is related to the circumferential mode shapes and frequencies of the stator and the magnitude of magnetic radial force exciting the machine. The magnetic radial force, mode frequencies, and generated noise are all functions of machine geometry, configuration, and material properties. Therefore, an appropriate design can minimize the acoustic-noise level of an SRM[16 ,17].In this work the SR motor is supposed to operate in a wide speed range from 300 to 5000 rpm as a 4/6 SR motor. Having 4 rotor poles and 6 stator poles causes 12 exciting per period. Therefore in order to avoid high amplitude vibration the stator must be designed in the way that its lowest natural frequency be higher enough 12 as much of motor speed. Considering the motor of maximum speed equal to *4000 (rpm)* the highest exciting frequencies is *1000 (Hz)*. Another acceptable estimation in the use of locally linear neurofuzzy modeling of natural frequencies of cylindrical shells in optimal design of SR motors is that stator of SR motor consist of stator yoke and stator teeth which is deferent from cylindrical shell. However the yoke alone might easily be considered as a cylindrical shell. In order to use the obtained model in this optimization purpose, one could find some similarities in relations for natural frequencies of bars and lumped masses and generalize them to cylindrical shells. It might be found out that in any structure:

$$Natural Frequency \propto \sqrt{\frac{Stiffness properties}{Inertia properties}} \quad (22)$$

The relation (20) which was used before confirms this idea. Thus it might be assumed that stator teeth have not significant role in the stiffness of whole stator in circumferential vibrations so this role can be ignored. Also the inertia property of stator teeth is considered by modifying the model of natural frequencies using the following inequality:

$$\text{Natural Frequency of Stator} \leq \text{Natural Frequency of Stator Yoke} \times \sqrt{\frac{\text{Mass of Stator Yoke}}{\text{Mass of Total Stator}}} \quad (22)$$

Here the goal is to find the stator shape with the least weight and the least consumed material while its first natural frequency is much higher than the upper bound of exciting frequencies of the stator by magnetic field. This bound was considered to be *3000 (Hz)* in the case of assuming *1000 (Hz)* as the highest exciting frequency. This constraint will guarantee avoiding resonance phenomena and high amplitude vibrations of motor (Stator and Frame are assumed to be an unique part with the same material and length as in [16-18]). Achieving this goal will done by means of Evolutionary programming.

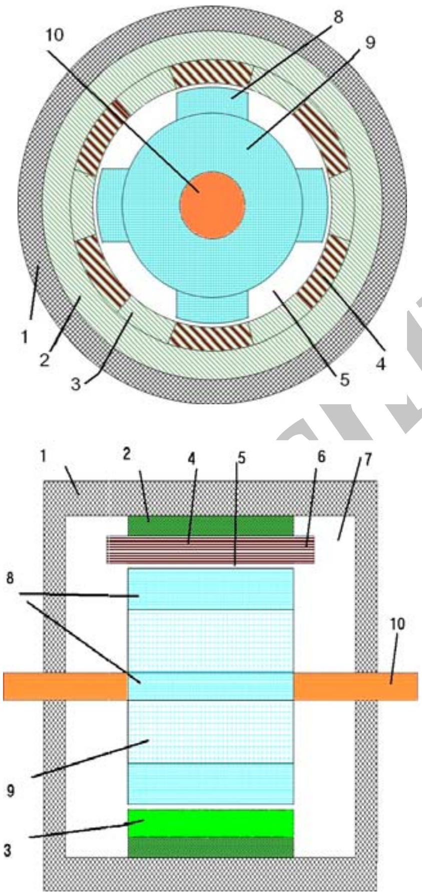

Figure 12- Two view of SR motor showing its various parts: 1-Frame 2-Stator yoke 3-Stator teeth 4-Windings 5-Air gap 6-Ending windings 7-Endcupping air 8-Rotor teeth 9-Rotor yoke 10-Axial shaft

7. Evolutionary algorithms

Evolutionary algorithms are optimization and search procedures inspired by genetics and the process of natural selection. This form of search evolves throughout generations improving the features of potential solutions by means of biologically inspired operations. Among the evolutionary algorithms, genetic algorithms behave much like biological genetics [19]. The genetic algorithms are an attractive class of computational models that mimic natural evaluation to solve problems in a wide variety of domains [19]. A genetic algorithm comprises a set of individual elements (the population size) and a set of biologically inspired operators defined over the population itself etc. Genetic algorithms manipulate a population of potential solutions to an optimization (or search) problem and use probabilistic transition rules. According to evolutionary theories, only the most suited elements in a population are likely to survive and generate offspring thus transmitting their biological heredity to new generations [19]. Genetic algorithms include following stages:

Selection: The purpose of parent selection in a GA is to give more reproductive chances to those individuals that are the fit. There are many ways to do it, but one commonly used technique is *roulette wheel parent selection* (RWS). A second very popular way of selection is *stochastic universal sampling* (SUS) which is used in this work.

Crossover (recombination): The basic operator for producing new chromosomes in the GA is that of crossover. Like in nature, crossover produces new individuals, which have some parts of both parents' genetic material. The simplest form of crossover is that of single–point crossover [19], which is used in the paper. The crossover probability is set to ρ_c .

Mutation: Mutation causes the individual genetic representation to be changed according to some probabilistic rule. For example, in the binary string representation, mutation causes a random bit to change its state. In natural evolution, mutation is randomly applied with low probability ρ_m , typically in the range 0.001 and 0.01, and modifies element in the chromosomes.

Reinsertion: Once selection and recombination of individuals from the old population have produced a new population, the fitness of the individuals in the new population may be determinate. If fewer individuals are produced by recombination than the size of the original population, than the fractional difference between the new and old population sizes in termed a generation gap. To maintain the size of the original population, the new individuals have to be reinserted into the old population. Similarly, if not all the new individuals are to be used at each generation or if more offspring are generated than size of old population then a reinsertion scheme must be used to determine which individuals are to exist in the new population.

Fitness function: In the optimization algorithms, a predefined fitness function should be optimized. In optimal design of switched reluctance motor the weight or volume of stator is the cost function which should be optimized using GA. Therefore, the fitness function may be inverse of it which must become maximum during optimization and the main constraint is that the natural frequencies of stator yoke must not interfere with the operation range of motor's speed for avoiding the resonance phenomena. In this case the fitness function will be equal to zero. It may be a question that why instead of any other cost functions such as losses, efficiency reduction or produced torque ripple, the weight of stator yoke is utilized without any consideration for electromagnetic relation. Because, in this case only the geometrical dimensions of "stator yoke" are going to be optimized while the dominant role in efficiency, produced torque, losses and other electromagnetic issues is played by variation of the air gap and teeth and slots geometrical dimensions. In the other word, the geometrical dimensions of the stator yoke are not of a great importance in variation of efficiency, produced torque, losses and etc. except its effects on the geometry of other parts of motor [21]. Consequently, radius, thickness and length of stator yoke are only of a great concern in motor volume and weight while the inner radius of stator yoke is restricted to a certain value which does not affect the other significant geometries.

According to mentioned algorithm the following result have been obtained via evolutionary programming:

Outer radius of stator yoke= 73 mm
Inner radius of stator yoke= 67 mm
Length of stator yoke= 100 mm

These results are obtained for 4/6 SR motor with *30 deg* for stator pole angle which is based on the geometries of the laboratory prototype in control lab of university of Tehran. The other geometries and characteristics of motor and its drive have been optimized in other research processes.

9. Conclusion

Solution of natural frequencies of cylindrical shells especially in some cases in which the assumption of thin-walled long cylinder is not valid, are not available. Also, Finite Element Method can not present a lumped model for natural frequencies of cylindrical shells, while a neurofuzzy network can be trained for estimation of a lumped model for the results of solution in Finite Element Method using the algorithm of (LOLIMOT), which have shown an excellent precision and speed. The proposed intelligent modeling can be applied for modeling of other mechanical behaviors of systems which are obtained through numerical methods. This might help the designer to evaluate the influence of various parameters on the systems characteristics as well as design optimization. Furthermore, the training algorithm of (LOLIMOT) can be used easily in any online application because of its excellent precision and speed. Also, in this paper modeling of natural frequencies of cylindrical shells was applied to optimal design of the stator of switched reluctance motor. In this way, stator weight was minimized by means of an evolutionary algorithm.

10. Acknowledgements

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