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Design Optimization of Permanent Magnet-Brushless DC Motor using Elitist Genetic Algorithm with Minimum loss and Maximum Power Density

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Abstract

In this paper, design optimization of Permanent Magnet-Brushless DC (PM-BLDC) motor is presented by using Elitist Genetic Algorithm (GA). For this purpose, three objective functions are considered i.e. total loss and power density of the motor and combinations of both. Aim of this paper is to optimize the motor with these three objective functions separately. The first two objective functions are single-objective but for the third case, multi-objective optimization is performed in which total loss and power density that are technically opposite are formulated into one single objective. Seven design variables including stator inner diameter (D), axial length of motor (L), pole pitch (τ_p), specific magnetic loading (B_{av}), specific electric loading (ac), stator back-iron length (h_{bis}) and stator slot height (h_s) are chosen as optimization variables. Optimization is carried out by Elitist GA which has a better performance in comparison with conventional GA. Optimization results show that multi-objective functions performs much better comparing to single-objective functions because more reliable and realistic design optimization would be carried out by multi-objective functions. At last, Finite Element Method (FEM) is used that its results have well validated the analytical design optimization.

Keywords: Permanent Magnet, BLDC Motor, Design Optimization, Multi-objective Optimization, Elitist Genetic Algorithm, Finite Element Method, Ansoft Maxwell.

1. Introduction

A permanent magnet-brushless direct current (PM-BLDC) motor has the highest performance in terms of power density and efficiency among different types of electrical motors. Employing PMs as

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excitation system removes copper winding and consequently no excitation loss is produced. This causes efficiency raise farther than motors with excitation winding. Brushless DC motors are similar to AC synchronous motors. The major difference is that synchronous motors develop a sinusoidal back EMF in comparison to a rectangular, or trapezoidal, back EMF of brushless DC motors. The stator of both types of motors has rotating magnetic fields that produce torque in rotor. The stator windings are like a poly phase AC motor, and the rotor has some permanent magnets. There are different configurations of PMs for rotor which are categorized into two types of mounted or internal PMs. On the other hand, brushless DC motors are usually fed by a square-wave current but AC synchronous motors are driven by sinusoidal current [1-5]. PM-BLDC motors are used in specific areas of electricity industry where high efficiency and desired performance are great of concern. However, performance characteristics of such motors could be further improved by design optimization. Through optimization, motors can be designed optimally. Therefore, desired performance of device is fulfilled and at last overall cost is decreased.

Optimal design of PM-BLDC motors is an important issue which has attracted researchers' attention. Several surveys have been done on BLDC motor design optimization in the literature [6–18]. For instance, Bora et al. [6] presented a new design approach for the Brushless DC wheel motor problem named Bat-Inspired optimization. The aim of the paper is to optimize the mono and multi-objective optimization problems related to the brushless DC wheel motor problems. A multi-objective PSO approach is proposed and applied in the design with the constraints presence of a brushless DC wheel motor in [7]. A novel topology optimization method for the material distribution of electrical machines using the Genetic algorithm combined with the cluster of material and the cleaning procedure is presented in [8]. A comparative study between three optimization approaches, i.e. classical gradient-based, direct search and GA, in BLDC motor design has been presented in [6]. A GA-based optimal design of a surface mounted permanent magnet BLDC motor has been proposed [7] in which the objective function includes permanent magnet (PM) characteristics, motor performance, magnetic stresses and thermal constraints. Hwang and Chang [8] have used electromagnetic field analysis based on the finite element method to design a high power density and high efficiency outer rotor BLDC motor to the applications of electric vehicles. A GA-based optimal design of a permanent magnet BLDC motor has been proposed [9], considering efficiency as the

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objective function and motor weight and temperature rise as the constraints. Markovic and Perriard [10] have suggested a simplified analytical method to design a small two-pole slotless BLDC motor. An experimental design method is reported to optimally design a BLDC motor [11] in which the optimization parameters are assumed to be stator yoke and magnet thickness.

This paper presents design optimization of surface-mounted PM-BLDC motor using Elitist Genetic Algorithm (GA). Elitist GA performs better comparing to the conventional GA. Total loss and power density (ratio of output apparent power to total volume of motor) are considered as objective functions. The first two objective functions are single-objective but the third one is multi-objective which is a combination of mentioned objective functions. Aim of this paper is to optimize the motor based on these three objective functions. Simulation results of Elitist GA show that, multi-objective optimization has better performance because it leads to practical solutions while results of single-objective optimization are not realistic.

The rest of paper is organized as follows:

Section 2 provides detailed description about PM-BLDC motors. Elitist GA is discussed in section 3 and optimization results are presented in section 4. For further clarification, optimization procedure is verified through employing finite element analysis (FEA) in section 5. At last paper is concluded in section 6.

2. PM-BLDC Motor

2.1. Geometry Description

Overall view of PM-BLDC machine is shown in Figure 1. As shown, surface-mounted PMs are placed onto the rotor. Multi-phase winding is wound in the stator slots which creates rotating magnetic field in the air gap of motor. Magnetic flux of PMs is crossed through the air gap and travels into the stator core and then returns back to rotor. Comparing to other PM configuration in PM-BLDC motors, surface-mounted PMs are one of proper configurations which gives required performance for motor. Internal PMs are good choice when the speed of motor is so high. In high-speed applications, centrifugal forces limit the use of surface-mounted PMs. However, surface-mounted PMs are better choice in normal applications [3, 4].

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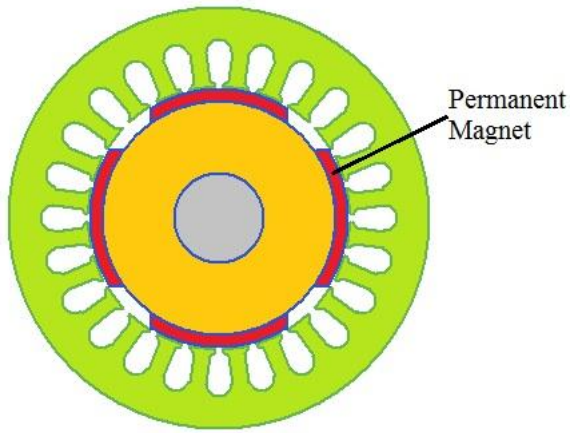

Figure 1: View of a PM-BLDC motor

2.2. Design Equations

In this paper, power density and efficiency are considered as objective functions. Therefore, equations related to these two objectives are extracted in this section.

In electrical machines, output power of machine is expressed as

$$Q = C_0 D^2 L n_s \ KVA \tag{1}$$

in which C_0 is Output coefficient that is formulated as follow

$$C_0 = 1.11 p^2 B_{av} a c K_W \times 10^{-3} \tag{2}$$

Besides, total volume of machine can be calculated as

$$V_T = \frac{\pi}{4}[D + 2(h_s + h_{bis})]^2 L \tag{3}$$

Efficiency is determined through the following equation

$$\eta = \frac{P_{out}}{P_{out} + P_{loss}} \tag{4}$$

where P_L, total loss, is expressed as

$$P_L = P_{cu} + P_c + P_{mech} + P_{stray} \tag{5}$$

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In which, P_{cu}, Total copper loss, is

$$P_{cu} = mR_s (I_s)^2 \tag{6}$$

where R_s and I_s are resistance and current of every phase, respectively. P_c, Core loss, can be calculated as follow

$$P_c = k_h f B_m^2 + k_e f^2 B_m^2 \tag{7}$$

where k_h and k_e are hysteresis and eddy constants. B_m is maximum flux density and f is frequency. Mechanical loss (Windage and friction loss) and stray loss are considered between 0.5 to 3 percent and 0.5 to 1 percent of the output power, respectively [1-5]. Parameters of motor are defined in Table 1.

Table 1: Parameter Description

Parameter	Definition
P_{out}	Output Power
P	Number of poles
n_s	Rated Speed
I_s	Phase Current
R_s	Phase Resistance
f	Frequency
D	Stator Inner Diameter
L	Motor Axial Length
ac	Specific electric loading
B_{av}	Specific magnetic loading
h_{bis}	Stator back-iron height
h_s	Slot height
τ_p	Pole Pitch
K_w	Winding factor

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3. Elitist Genetic Algorithm

One of the most reliable and efficient optimization algorithms is Genetic Algorithm (GA) which is widely used in so many engineering optimization problems. GA is a programming method that mimics biological evolution as a problem solving strategy based on Darwinian's principle of evolution and survival of fittest to optimize a population of candidate solutions towards fitness. GA uses an evolution and natural selection that uses a data structure like chromosomes and evolve the chromosomes, using selection, crossover, and mutation operators. The process of GA begins with a random population of chromosomes, which represent all possible solution of a problem that are assumed as candidate solutions. The size of the population is depended to the size and the nature of the problem. The locations of each chromosome are encoded as characters or numbers and could be referred to as genes. Then according to the desired solution an evaluation function is used to calculate the goodness of each chromosome known as "Fitness Function". Two basic operators, crossover and mutation, are used to simulate the natural reproduction and mutation of species during evaluation. The main aim of crossover is to search the parameter space and it is the most important operator in GA. The crossover operator takes two strings from the old population and exchanges the next segment of their structures to form the offspring.

The function of mutation is used to prevent the loss of the information. Mutation can keep the population more diverse so that it alters a string locally to create a better string. Once the new proportion is completed, the program will continue to generate new population. The iteration can be stopped while no further significant change of the solution occurs or when the specified number of iteration is reached. The Selection of chromosomes for survival and combination is biased towards the fittest chromosomes. A GA generally has four components. A population of individuals represents a possible solution. A fitness function which is an evaluation function by which we can tell if an individual is a good solution or not. A selection function decides how to pick good individuals from the current population for creating the next generation. Genetic operators such as crossover and mutation which explore new regions of search space while keeping some of the current information at the same time [19]. The idea of elitism in GA provides a new property to the

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selection process. In elitist GA, best genome of each population would be alive and exists in the next population. In other words, the genome with highest fitness will be transferred into the new population automatically. Applying elitism in GA improves its performance. In this paper, there are some considerations for algorithm which are categorized in Table 2.

Table 2: Parameters of GA

Parameter	Value
Number of Variables	7
Number of Generations	500
Number of Genomes	200
Probability of Reproduction	0.1
Probability of Cross Over	0.7
Probability of Mutation	0.1
Probability of Shift	0.1

4. Optimization Results

Three different Objective functions are defined for this study; total loss, power density and combination of both. Seven variables are chosen as design variables. These variables together with their maximum and minimum ranges are listed in Table 3.

Table 3: Minimum and maximum ranges of design variables

Variable	Min	max
D (mm)	50	90
L (mm)	60	100
τ_p (mm)	40	80
B_{av} (T)	0.4	0.9
ac (A/m)	8000	30000
h_{bis} (mm)	5	15
h_s (mm)	10	25

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4.1. Total Loss

Total loss is expressed in terms of design variables which should be minimized:

$$P_L = \left\{ mR_s (I_s)^2 + [(k_h B_m^{1.6} f) + (k_e B_m^2 f^2)] + 0.005 P_{out} + 0.01 P_{out} \right\} \quad (8)$$

Figure 2 shows total loss versus iteration. Optimum value for total loss is 45.6209 which is converged after 52 iterations. Optimal design variables are listed in Table 4. It is clear that in cases when minimized loss is needed, design of machine is an iron design. As given in Table 4, specific magnetic loading (B_{av}) is quite higher comparing to specific electric loading (ac). This shows that, in these cases machine design is an iron design. On the other side, as expected most of the variables are selected near to their minimum value.

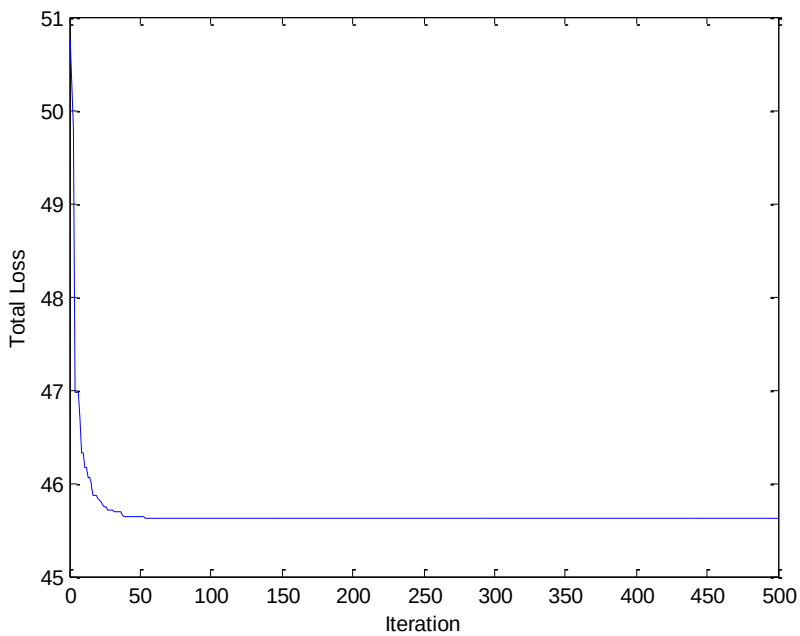

Figure 2: Total loss versus iteration

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Table4: Optimal values of design variables for minimizing Total loss

Variable	Min
D (mm)	55.2
L (mm)	74.5
τ_p (mm)	53.1
B_{av} (T)	0.742
ac (A/m)	16230
h_{bis} (mm)	9.8
h_s (mm)	14.6

4.2. Power Density

Power density is the ratio of output apparent power (Q) to total volume of motor (V_T) which is formulated as below:

$$PD = (1.11p^2 B_{av} acK_W D^2 Ln_s) / (\frac{\pi}{4}[D + 2(h_s + h_{bis})]^2 L) \quad (9)$$

This objective is to be maximized. It means that, motor operates in the highest possible power with least volume. Figure 3 shows power density versus iteration. Optimum value for power density is $3.3*10^8$ W/m^3 which is converged after 120 iterations. In this case, power density has to be increased. In the objective function, parameter L is emitted, so it has no role to determine the overall fitness of the objective. Table 5 gives optimal values for design variables. As expected, most of the variables are chosen near to their maximum value. This is because of the fact that, objective function has to be maximized.

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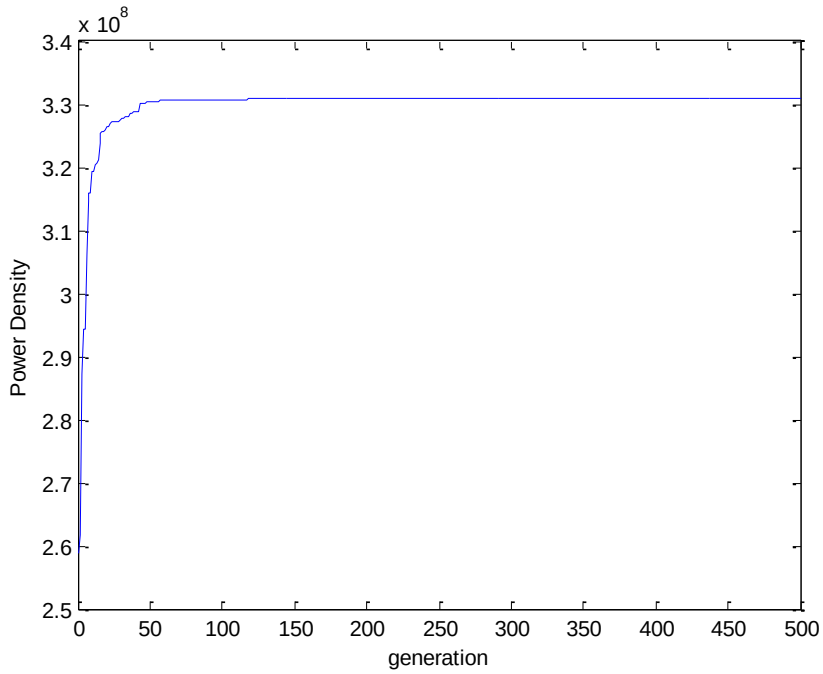

Figure 3: Power density versus iteration

Table 5: Optimal values of design variables for maximizing power density

Variable	Min
D (mm)	77.3
L (mm)	80.23
τ_p (mm)	67.15
B_{av} (T)	0.834
ac (A/m)	27630
h_{bis} (mm)	10.7
h_s (mm)	12.65

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4.3. Combinatorial Objective Function

In two abovementioned sections, single objective functions were considered. As illustrated, single objectives would not determine the real performance of machine well enough, because in each device there are parameters opposite to each other. In this section, combinatorial objective function is presented. This objective function is a combination of total loss and power density that is calculated as below

$$\min f(x) = \left(\frac{P_L}{P_L^{\max}}\right) - \left(\frac{PD}{PD^{\max}}\right) \tag{10}$$

Total loss and power density are two opposite parameters. It is clear that, total loss should be minimized and power density should be maximized. Therefore, the equation (10) is suggested which combines these two opposite parameters together. This is a multi-objective problem which is converted into a single-objective problem by proper weighting to the objectives. In equation (10), P_L^{max} is optimal solution to the problem of minimizing total loss and PD^{max} is optimal solution to the problem of maximizing power density regarding variables range. Therefore, both objectives would have an identical scale. The whole objective has to be minimized. Objective function f(x) versus iteration is shown in Figure 4. Optimal values of design variable are presented in Table 6. Besides, power density, total loss and best fitness are obtained in Table 7.

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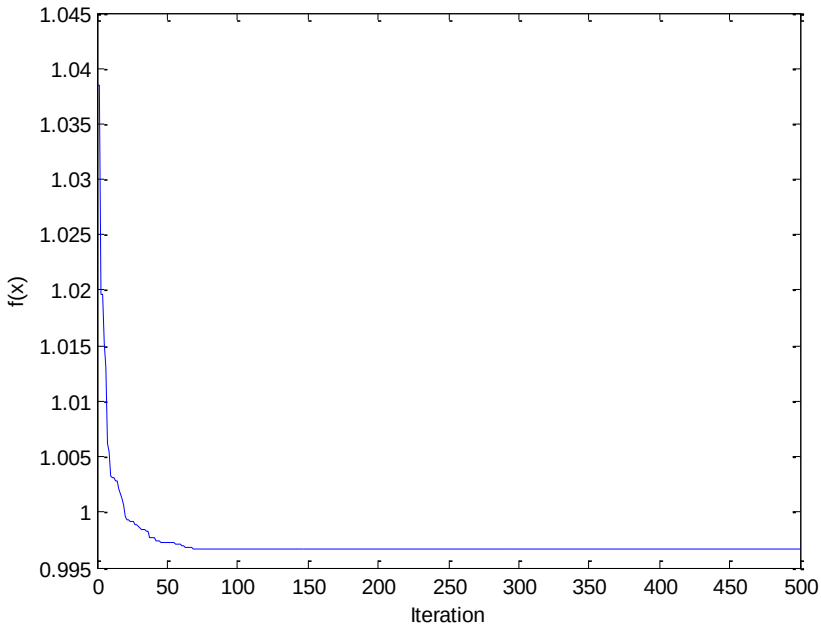

Figure 4: Objective Function f(x) versus iteration

Table 6: Optimal values of design variables for minimizing f(x)

Variable	Min
D (mm)	71.67
L (mm)	75.55
τ_p (mm)	62.4
B_{av} (T)	0.7854
ac (A/m)	24113
h_{bis} (mm)	10.4
h_s (mm)	12.95

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Table 7: Design Outputs for combinatorial objective function, f(x)

Parameter	Value
P_L (W)	74.7
PD (W/m^3)	1.1e6
Best Fitness	0.9955

5. Finite Element Method

The optimal design of the motor is a pure analytical research. Therefore, there should be a criterion to validate the accuracy of the design optimization. In this section, finite element method (FEM) is used for this purpose. Ansoft Maxwell is one of the most important and efficient softwares which is based on FEM analysis. The dimensions and parameters obtained by design optimization would be given to the software. A 2D FEM simulation is carried out and the numerical and graphical results are obtained. Figure 5 shows finite element mesh of the motor. Figure 6 shows magnetic flux lines diagram. Flux lines are started from rotor core and pass through tooth and yoke of stator and then returns back to rotor. Figure 7 and 8 show magnetic flux density distribution and flux density vector of motor. It was assumed that in analytical design process, maximum flux density in stator yoke is 1.6 T. Based on Figure 7, it is clear that FEM simulation verifies this assumption with a little degree of error. Hence, analytical design optimization is accurate and logical.

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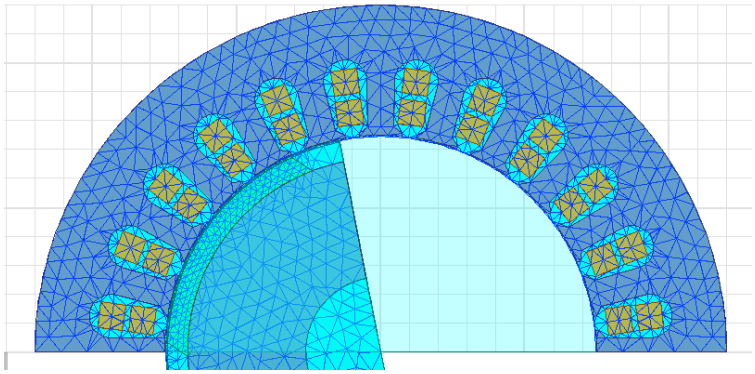

Figure 5: Finite element mesh

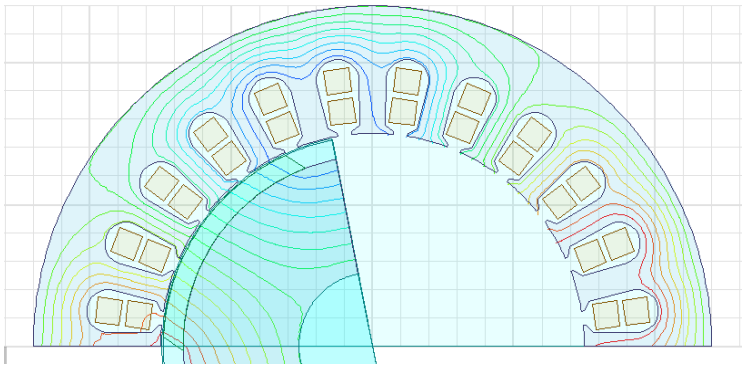

Figure 6: Magnetic flux lines diagram

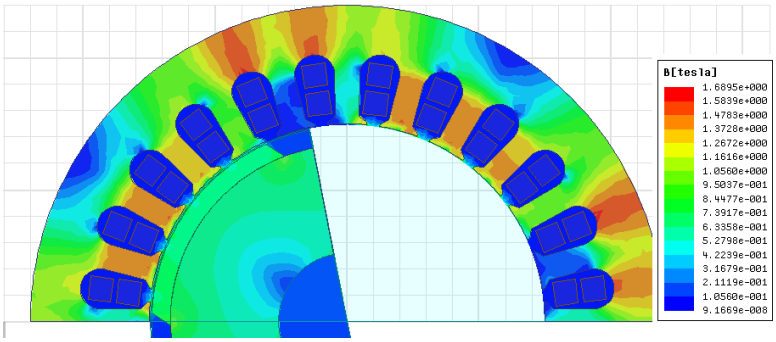

Figure 7: Magnetic flux density distribution

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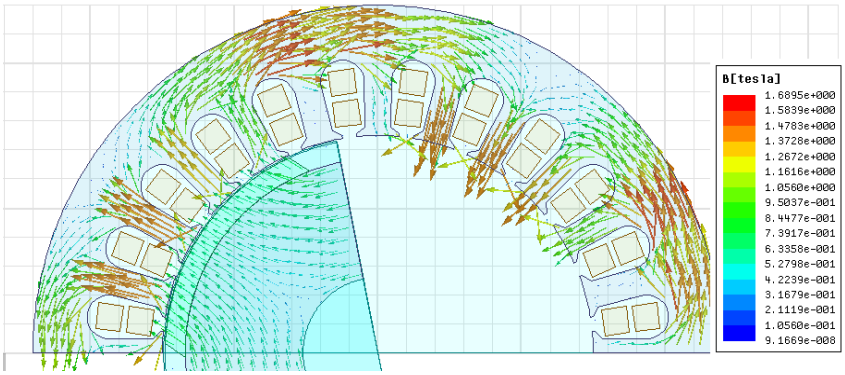

Figure 8: Magnetic flux density vector

Conclusion

Optimum design of Permanent Magnet-Brushless DC (PM-BLDC) motor was investigated in this paper. Three objective functions were considered by use of Elitist Genetic Algorithm (GA). First of all two single objectives were optimized i.e. minimizing total loss of motor and maximizing power density of motor, respectively. It was shown that in the two first cases, optimization is carried out in a unidirectional path and design variables are not chosen technically well. In third case, multi-objective optimization was performed in which the combinatorial objective function was composed of total loss and power density of motor together. These two opposite objectives were converted into a single objective. In this case, design variables are selected more realistic. In fact, design variables are limited by minimizing total loss and maximizing power density, simultaneously. This shows better performance of multi-objective functions comparing to single-objective functions. Finally, finite element method (FEM) was implemented to confirm the analytical optimization. Simulation results of FEM showed that the results of analytical optimization are in good agreement with those obtained by FEM. Future works may be devoted to further investigate more complex objective functions with more design variables.

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Available online at: http://www.aeuso.org

References

[1]. H. A. Toliyat, G. B. Kilman, "Handbook of Electric Motors", CRC Press, 2nd Edition, 2004.

[2]. E. S. Hamdi, "Design of Small Electrical Machines", John Wiley & Sons, 1994.

[3]. J.R. Hendershot, T.J.E. Miller, "Design of Brushless Permanent-Magnet Machines", Motor Design Books. LLC, 2nd Edition, 2010.

[4]. W. Yeadon, A. Yeadon, "Handbook of Small Electric Motors", McGraw-Hill Professional, 1st Edition, 2001.

[5]. B.K. Lee, M. Ehsani, "Advanced Simulation Model for Brushless DC Motor Drives", Electric Power Components and Systems 31, 841–868, 2003.

[6]. T. C. Bora, L. D. S. Coelho, L. Lebensztajn, "Bat-Inspired Optimization Approach for the Brushless DC Wheel Motor Problem", IEEE Transactions on Magnetics, vol.48 , no. 2, pp. 947–950, Feb. 2012.

[7]. L. D. S. Coelho, L. Z. Barbosa, L. Lebensztajn, "Multi-objective Particle Swarm Approach for the Design of a Brushless DC Wheel Motor", IEEE Transactions on Magnetics, vol.46 , no. 8, pp. 2994-2997, Aug. 2010.

[8]. T. Ishikawa, K. Nakayama, "Topology Optimization of Rotor Structure in Brushless DC Motor With Concentrated Windings Using Genetic Algorithm Combined With Cluster of Material", IEEE Transactions on Magnetics, vol.48 , no. 2, pp. 899 - 902, Feb. 2012.

[9]. M. Markovic, P. Ragot, Y. Perriard, "Design optimization of a BLDC motor: a comparative analysis", in Proc. IEEE International Electric Machines and Drives Conference, Turkey, 2007, pp. 1520-1523.

[10]. N. Bianchi, S. Bolognani, "Brushless DC motor design: an optimization procedure based on genetic algorithms", in Proc. International Conference on Electrical Machines and Drives, UK, 1997, pp. 16-20.

[11]. C.C. Hwang, J.J. Chang, "Design and analysis of a high power density and high efficiency permanent magnet DC motor", Journal of Magnetism and Magnetic Materials 209 (2000) 234–236.

[12]. P.R. Upadhyay, K.R. Rajagopal, "Genetic algorithm based design optimization of a permanent magnet brushless DC motor", Journal of Applied Physics 97 (10) (2005) Article No. Q516.

[13]. M. Markovic, Y. Perriard, "Simplified design methodology for a slotless brushless DC motor", IEEE Transactions on Magnetics 42 (12) (2006) 3842–3846.

[14]. S. Vivier, F. Gillon, P. Brochet, "Optimization techniques derived from experimental design method and their application to the design of a brushless direct current motor", IEEE Transactions on Magnetics vpl.37, no.5, pp. 3622–3626, 2001.

[15]. A. Rahideh, T. Korakianitis, P. Ruiz, T. Keeble, M.T. Rothman, "Optimal brushless DC motor design using genetic algorithms", Journal of Magnetism and Magnetic Materials 322 (2010) 3680–3687.

International Journal of Mechatronics, Electrical and Computer Technology

Vol. 4(10), Jan, 2014, Special Number, pp. 1169-1185, **ISSN**: 2305-0543
Available online at: http://www.aeuso.org

[16]. W. Zhu, X. Yang, Z. Lan, ”Structure Optimization Design of High-speed BLDC Motor Using Taguchi Method”, in Proc. International Conference on Electrical and Control Engineering (ICECE), 25-27 June 2010.

[17]. J. G. Junak, Ombach, ”Performance optimization of the brushless motor with IPM rotor for automotive applications”, in Proc. International Conference on Electrical Machines - ICEM 2010, Rome.

[18]. T. Tusar, P. Korosec, G. Papa, B. Filipic, J. Silc, ”A comparative study of stochastic optimization methods in electric motor design” Applied Intelligence 27 (2) (2007) 101–111.

[19]. A. P. Engelbrecht, “Computational Intelligence: An Introduction”, John Wiley & Sons, 2007.

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