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A fuzzy-genetic based design of permanent magnet synchronous motor

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Abstract: This paper presents a fuzzy-genetic based design of permanent magnet synchronous motor. The selected motor structure with surface magnet and double layer winding is for high torque and low speed applications. The design approach involves combining fuzzy logic and genetic algorithm in a powerful combination. While the genetic algorithm is used in scanning of the solution space, the fuzzy logic approach has been utilized in selecting the most appropriate solutions. While choosing geometric parameters as input for optimization, design equations are obtained by using geometrical, electrical and magnetic properties of the motor. The output results are evaluated with motor efficiency, motor weight and weight of magnets as the objective function. Furthermore, the multiobjective design optimization results are compared with the results obtained for each single objective and tested with a finite element program. The results are finally remarkable and quite compatible with the finite element results.

Keywords: Design optimization, fuzzy-genetic approach, permanent magnet synchronous motor

1. Introduction

Induction motor and permanent magnet synchronous motor (PMSM) are among the most used electric motors in industrial fields. While induction motors are of interest because of their low cost and ease of maintenance, permanent magnet synchronous motors have high power density and high efficiency. In addition, in today's control applications, drive systems affect the motor selection. After all, whatever the performance criteria, due to high efficiency it is clear that the use of PMSMs is increasing. Most prominent feature of PMSMs is that they show structural differences according to the placement of the magnets. Naturally this affects the performances and the production costs of PMSMs. Due to the ease of design and low production cost, surface mounted PMSMs are the most preferred types for low speed applications. This structure is also preferred because of its low cogging torque based on slot and pole combination [1].

The design of electric motors is the most complex engineering problem. It is because the electric motors have the non-linear structures. To overcome this situation, when some simplifications are taken, linear equations are used in electric motor design studies. This is even more preliminary in optimization applications wherein artificial intelligence algorithms are used. In academic or industrial fields complex and realistic designs are provided by commercial programs using finite element method. In fact, analytically and numerically, two methods are basically applied in the design of electric motors. Working with the analytic equations is weak in terms of accuracy but advantageous in terms of duration. On the other hand working with the numerical methods such as finite element method is effective in terms of correctness of the results but weak in terms of duration [2]. Nevertheless, in the design optimization studies where analytic equations are used, electric motor designs can be flexibly directed to single objective or multiobjective.

With a general evaluation, the design optimization studies which artificial intelligence used are based on the effectiveness of the algorithms. One of them is undoubtedly the most recognizable genetic algorithm. This algorithm has been applied to so many different electric motor design problems up to date [3-5]. In addition, the more strong algorithms constructed by combining the different artificial intelligence algorithms or other methods with genetic algorithm have been used [6-9].

The designs of permanent magnet synchronous motors are more complex and non-linear engineering problems and also contain some fuzzy facts such as other electric motor designs [10, 11]. The fuzzy-genetic approach is quite useful in terms of decision structure and ease of application in the choice of objective function. By using the fuzzy-genetic structure, a large solution space can be scanned and the designer's experience, view and judgment are well reflected [10-14]. In this study, as multiobjective, a fuzzy-genetic based approach was firstly used in the design optimization of the surface mounted permanent magnet synchronous motor. Motor efficiency, motor weight and weight of magnets were selected as objective function and then the objective and constraint values were determined by using fuzzy rules. Single and multi objective optimization results were given comparatively, and the results were tested by a finite element program. The effects of the fuzzy-genetic structure used were shown in the PMSM design with graphics and tables. In this respect, PMSM design optimization has been examined in a versatile way and useful inferences have been provided for the technical staffs.

2. Multidirectional Analysis of The PMSM

Electrical, magnetic, thermal and mechanical analyzes are carried out in the designs of electric motors. The solution of the differential equations obtained for each analysis is quite complex. Moreover, due to the non-linearity of the electric motors, it is almost impossible to do very precise solutions. Numerical methods such as finite element method are used in this case. Obviously, the use of linear equations for a basic design is sufficient. The geometrical model of the PMSM, the electrical and the magnetic circuits are investigated in each subdivision as follows.

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2.1. The Geometric Model

The use of magnetic and electrical equations commonly associated with the geometric modelling in the designs of electric motors is widespread. Such approaches are primitive but provide rapid analysis [2]. In this study based on the geometric model of the PMSM has 12 slots and 10 poles shown in Figure 1. By some assumptions, the objective functions are obtained with the help of magnetic and electric equations. Facilitating acceptance is the result of an optimal design that sets the grounds for these assumptions.

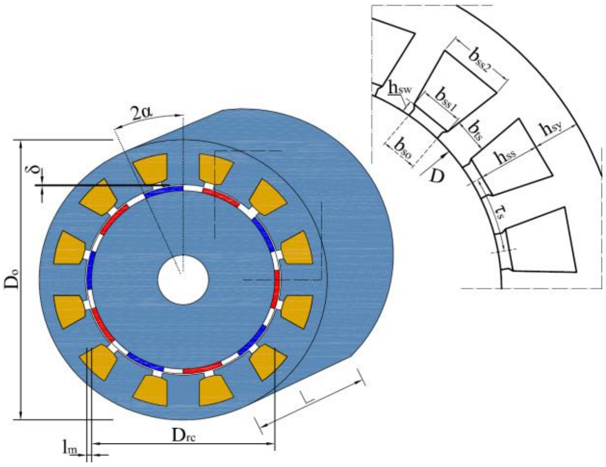

Figure 1. 3D geometric model of the PMSM

2.2. The Magnetic Circuit

According to the magnetic circuit in Figure 2 [1, 2] it is very difficult to calculate the magnetic flux in each region of the PMSM. The most important issue in the magnetic design is the accurate calculation of air gap magnetic flux [15]. The magnetic flux at the points on the stator and the rotor is particularly important in terms of saturation. From this point of view, magnetic boundary values are the points to be considered in the PMSM design. Magnetic flux density equations of air gap, stator tooth, stator yoke and rotor yoke are as follows.

$$B_m = (B_r k_{leak} l_{\mathrm{m}})/(l_{\mathrm{m}} + \mu_r \delta k_C) \quad (1)$$

$$\hat{B}_\delta = (4/\pi) B_m \sin\alpha \quad (2)$$

$$B_{st} = \left(4\alpha B_m (D/2-\delta)(1-k_{leaktooth})\right)/(2pqb_{st} stfc) \quad (3)$$

$$B_{sy} = \left(4\alpha B_m (D/2-\delta)\right)/\left(2ph_{sy} stfc\right) \quad (4)$$

$$B_{ry} = \left(4\alpha B_m (D/2-\delta)\right)/\left(2ph_{ry} stfc\right) \quad (5)$$

where, remanence flux density of permanent magnet is B_r, maximum of air gap flux density is B_m, fundamental of air gap flux density is $\hat{B}_\delta$, flux density in a stator tooth is B_{st}, flux density in stator yoke is B_{sy}, flux density in rotor yoke is B_{ry}, correction factor for air gap flux density is k_{leak}, relative magnet permeability is μ_r, Carter factor is k_C, pole angle is 2α, inner stator diameter is D, correction factor for flux density in stator teeth is $k_{leaktooth}$, number of slots per pole per phase is q, stacking factor of the stator iron laminations is $stfc$, stator yoke height is h_{sy}, rotor yoke height is h_{ry}.

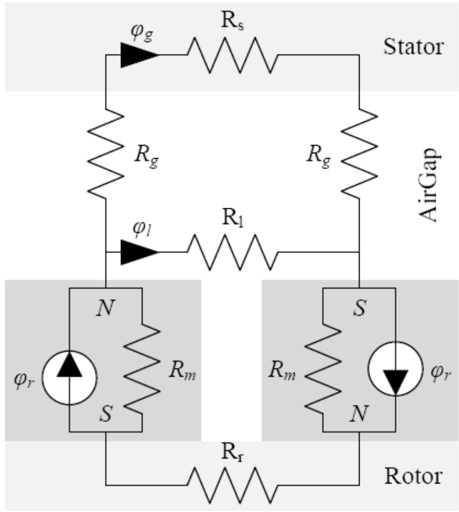

Figure 2. Magnetic circuit for the geometrical model of the PMSM

2.3. The Electrical Circuits

Electromechanical conversions are the most important part of electrical circuit design. Here, the motor d-q electrical circuits at base speed (Fig. 3) and the equations were given. When the moment equation is examined, the number of windings of the motor is calculated only according to the I_q current because the I_d current is zero in the non-salient permanent magnet synchronous motors [16, 17].

$$\hat{E} = \omega k_{\omega 1} q n_s \hat{B}_\delta L(D-\delta) \quad (6)$$

$$R_{Cu} = \left(\rho_{Cu}\left(pL + \pi k_{coil}(D + h_{ss})\right) n_s^2 q\right)/f_s A_{sl} \quad (7)$$

$$L_{d,q} = (pq\lambda + 3/\pi\,(qk_{\omega 1})^2\,(D-\delta)/(\delta k_C + l_m/\mu_r))\mu_0 L n_s^2 \quad (8)$$

$$\hat{U} = \sqrt{U_q^2 + U_d^2} = \sqrt{\left(\hat{E} + R_{Cu} I_q\right)^2 + \left(L_q \omega I_q\right)^2} \quad (9)$$

where, electrical angular frequency is ω, fundamental winding factor is$k_{\omega 1}$, conductor number per slot is n_s, stack length is L, copper wire resistivity is ρ_{Cu}, end-winding coefficient is k_{coil}, slot fill factor is f_s, slot area is A_{sl}, specific permeance coefficient of the slot opening is λ, d,q-axes terminal voltages are is $U_{d,q}$, d,q-axes currents are $I_{d,q}$, fundamental of the induced voltage is $\hat{E}$, winding resistance is R_{Cu}, d,q-axes magnetizing inductance is $L_{d,q}$.

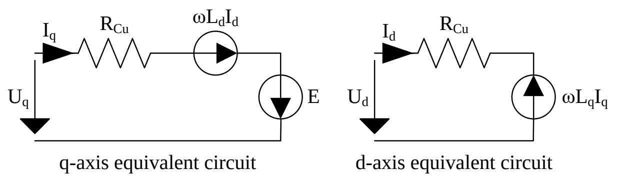

Figure 3. d-q equivalent circuits of the PMSM

2.4. The Objective Functions

The efficiency is generally the primary objective in the design of the electrical motor today. To improve efficiency in design studies, the reduction of copper losses is especially required for low-frequency multi-poles PMSMs. It is also necessary to pay more attention to one issue that the gearless PMSMs are more efficient than other electric motors with gears.

Motor weight and weight of magnets affect the cost as much as it is important in terms of the usage place. The permanent magnets are structurally the most expensive parts of the PMSMs, and their prices are also rapidly changing, especially due to technological developments. The weight of magnets improves the power density of the PMSMs and but increases the motor weight. Especially this situation is overwhelmed by multi-poles PMSM structures.

Three objective functions, namely motor efficiency, motor weight and weight of magnets, were used for the fuzzy-genetic based multiobjective design optimization. A suitable association for all objectives was aimed, namely to increase the motor efficiency, to reduce the motor weight and to reduce the weight of the magnets. The acquisition of these functions is a very detailed process and therefore references to different studies have been made [1, 2, 16-19]. As a result, the objective functions required for this study were obtained in the following order, motor efficiency, motor weight and weight of magnets.

$$\eta = P_{out}/(P_{out} + P_{Cu} + P_{Fe}) \tag{10}$$

$$W_{Tot} = W_{Shaft} + W_{PMs} + W_{Rotor} + W_{Stator} + W_{Winding} \tag{11}$$

$$W_{PM} = \rho_{PM} 4\alpha L l_m (D_{rc} + l_m) \tag{12}$$

where, efficiency is η, output power is P_{out}, copper losses is P_{Cu}, iron losses are P_{Fe}, total motor weight is W_{Tot}, shaft weight is W_{Shaft}, rotor weight is W_{Rotor}, stator weight is W_{Stator}, winding weight is $W_{Winding}$, weight of magnets is W_{PMs}.

3. The Fuzzy-Genetic Based Multiobjective Approach

The genetic algorithm has been applied to so many different electric motor design problems up to date [3-5]. In addition, the more strong algorithms constructed by combining the different artificial intelligence algorithms or other methods with genetic algorithm have been used [6-9]. In addition, the fuzzy-genetic approach has been used to solve some engineering problems such as selection of control parameters and induction motor design and so effective solutions have been made. Here, the definition and basic steps of the used fuzzy-genetic based multiobjective approach with the genetic algorithm are as follows [20, 21]:

$$\begin{aligned} &findX which\ maximize/minimize\ f(X) \\ &\quad subjectto; \quad h_m(X) = 0, \qquad m = 1,2,\dots,M \\ &\qquad\qquad\qquad g_j(X) \le 0, \qquad j = 1,2,\dots,J \\ &\qquad\qquad\qquad X_k^l \le X_k \le X_k^u, \qquad k = 1,2,\dots,K \end{aligned}$$

where objective functions form the multiobjective function vector as $f(x) = [f_1(X), f_2(X), \dots, f_n(X)]$, $h_m(X)$ and $g_j(X)$ are equality and inequality constraint functions. X_k^u and X_k^l are the upper and lower boundary values of the input parameter. The fuzzy objective is obtained by using the actual objective function values within the fuzzy boundaries. It uses the fuzzy membership s-function defined below.

$$\mu_{fi}(X) = \begin{cases} 0 & if\ f_i(X) \le f_i^{min} \\ 1 - 2\left(\frac{f_i(X) - f_i^{min}}{f_i^{max} - f_i^{min}}\right)^2 & if\ f_i^{min} < f_i(X) \le \left(f_i^{max} + f_i^{min}\right)/2 \\ 2\left(\frac{f_i^{max} - f_i(X)}{f_i^{max} - f_i^{min}}\right)^2 & if\ \left(f_i^{max} + f_i^{min}\right)/2 < f_i(X) \le f_i^{max} \\ 1 & if\ f_i^{max} \le f_i(X) \end{cases} \tag{13}$$

where $\mu_{fi}(X): \mathcal{R}^n \to [0,1]$ and it represents fuzzy correctness according to input parameters, f_i^{max} and f_i^{max} expressions are user-dependent minimum and maximum objective values. The fuzzy values of the objective function and the constraint values for fuzzy decision making must be calculated, and the conclusion for the constraint function is as follows.

$$\mu_{gj}(X) = \begin{cases} 0 & if\ g_j(X) > b_j + d_j \\ 1 - \left(g_j(X) - b_j\right)/d_j & if\ b_j \le g_j(X) \le b_j + d_j \\ 1 & if\ g_j(X) < b_j \end{cases} \tag{14}$$

where $\mu_{gj}(X): \mathcal{R}^n \to [0,1]$ and it represents fuzzy constraints according to input parameters. b_j is the desired value, d_j is the tolerance value.

3.1. Fuzzy Decision Making

The aim of the multiobjective optimization is to find the best solution by using linearized fuzzy objective and constraint membership functions. That is to find a solution with maximum membership from the fuzzy solution space. This situation can be shown as follows [20, 22]:

$$\mu_D(X^*) = \max\left(\mu_D(X)\right),\ \mu_D \in [0,1] \tag{15}$$

Convex fuzzy decision criterion was chosen in this study. Convex decision is an approach that depends on the arithmetic mean and the weight of each fuzzy objective function. As shown below.

$$D = \alpha f(X) + \beta g(X) \tag{16}$$

where α and β are weighting factors, which satisfy

$$\alpha + \beta = 1 \quad (\alpha \ge 0\,;\ \beta \ge 0) \tag{17}$$

These coefficients can be obtained by the linear weight average of the objective functions. Thus, the membership function is provided for convex fuzzy inference.

$$\alpha_i = \mu_{fi}/\textstyle\sum_{i=1}^{n} \mu_{fi}\ and \beta_j = \mu_{gj}/\sum_{j=1}^{m} \mu_{gj} \tag{18}$$

$$\mu_D(X) = \textstyle\sum_{i=1}^{n} \alpha_i \mu_{fi} + \sum_{j=1}^{m} \beta_j \mu_{gj} \tag{19}$$

where α_i and β_j satisfy

$$\textstyle\sum_{i=1}^{n} \alpha_i + \sum_{j=1}^{m} \beta_j = 1 \qquad \begin{matrix} \alpha_i \ge 0 & i = 1,2,\dots,n \\ \beta_j \ge 0 & j = 1,2,\dots,m \end{matrix} \tag{20}$$

The multiobjective design algorithm used here includes properties of fuzzy logic and genetic algorithm. While fuzzy logic approach reflects human thought in selecting the best result of the solution spaces, genetic algorithm tries to find the most appropriate result in a large solution space. Hence, the hybrid algorithm will strongly reflect the goals of the motor design.

The starting point is the geometric parameters in multiobjective design optimization. Selected geometric parameters are independent variable. Supply voltage, motor power and speed, etc. the quantities are invariable. Other design parameters are dependent variable. The objective functions were obtained by using the geometrical model, electrical and magnetic circuits of the motor. The most important aspect of optimization studies is the necessity of achieving objective functions with great accuracy. Objective functions for fuzzy multiobjective design optimization are formulated in different forms and compared with single objective studies with genetic algorithm. These formulations are shown in Table 1.

Table 1. Objective functions for the design optimization

Single objective functions	Multiobjective functions
f_1(to increase motor efficiency)	$F_1: max[\mu f_1, \mu f_2]$
f_2(to reduce motor weight)	$F_2: max[\mu f_1, \mu f_3]$
f_3(to reduce magnet weight)	$F_3: max[\mu f_1, \mu f_2, \mu f_3]$

The boundary values for fuzzification of the selected objective functions are given in Table 2. The appropriate values and tolerances for fuzzification of the constraints are given in Table 3.

Table 2. Boundary values of the objective functions for fuzzification

Objective Functions	Min value	Max value
$f_1(\%)$	0	100
$f_2(kg)$	50	150
$f_3(kg)$	0	3

Table 3. Constraint values and tolerances for fuzzification

Constraint	Desired value $(\boldsymbol{b_j})$	Tolerance value $(\boldsymbol{d_j})$
Stator tooth flux (B_{st})	1.6T	0.4T
Stator yoke flux (B_{sy})	1.4T	0.4T
Rotor yoke flux (B_{ry})	1.4T	0.4T

3.2. Steps of the optimization algorithm

The multiobjective function can be written as Eq. 21 and the flowchart of the optimization algorithm and the content of each step were explained in detail.

$$max(\mu_{D_i}) = \sum_{i=1}^{n} \alpha_i \mu_{fi} + \sum_{j=1}^{m} \beta_j \mu_{gj} \qquad (21)$$

It is not important to produce the first population, because the performance of artificial intelligence algorithms such as genetic algorithm is not dependent on initial population or individuals. However, the performance of the algorithm is affected by real-valued or binary coding [23], where the binary code was used for software ease. Also, since electric motor design studies require a lot of equations, the boundaries of the independent variables must be carefully chosen according to experience and requirements. The geometrical, electrical and magnetic equations are interaction with each other. It is therefore an effective approach to derive design equations by making use of design experience to make some negligence or to reduce motor design equations by using coefficients. Thus, an effective and useful approach for the designer will be achieved.

The obtained objective values are evaluated according to the previously described fuzzy decision approach. In this way, new populations are provided for the objective of the genetic algorithm and higher values are preserved. The termination criterion for the genetic algorithm was given as the iteration number or it could be the precision of the objective values. The important point here is to achieve the objectives with great accuracy.

The characteristics of the genetic algorithm and how it works are as follows [23-25].

i. It works to select the best individual (solution) and more solution is produced with the population for the optimization problem. Individuals in the population are independent of each other, whereas individuals are made up of genes that contain the solution of each independent variable. The population size and the number of genes are related to the direct input parameters, which influences the solution accuracy [17].

ii. Genetic algorithms carry the genetic properties of individuals to new populations by using the fitness function. Due to natural selection, strong individuals are more fortunate to survive from weaker individuals. This situation is repeated in each iteration to converge to the optimal solution.

iii. Genetic algorithms do not guarantee the optimal solution. Unfortunately, genetic algorithms can converge to a local solution. Genetic algorithms have reproduction, crossover and mutation operators. Using roulette wheel, tournament, or different crossover operators, individuals with high fitness values are selected. The crossover operator randomly changes the genes of two selected individuals. The mutation operator changes the gene of the preselected individual to "0" or vice versa for binary coding. In this way, the algorithm is prevented from converging with local solutions.

4. The Design Application and The Evaluation of The Results

Some constants must be predetermined in the design optimization. In this study permanent magnet synchronous motor with concentrated double layer winding has 340 volts of supply voltage, 2400 watts of shaft power, 250 rpm and also outer stator diameter is 300mm, stack length is 120mm and electrical magnet angle is 126°. After the invariables determined, variables and their boundary values was given in Table 4. The variable number was chosen to be sufficient for the geometry of the PMSM. Incorporating too many variables into the algorithm will affect sensitivity of the results and the optimization time.

Table 4. Input variables of the design optimization

Parameter	Symbol	Lower boundary	Upper boundary
Magnet thickness (mm)	l_m	3.5	5.5
Air gap length (mm)	δ	1	1.5
Slot wedge height (mm)	h_{sw}	0.5	3
Stator tooth width (mm)	b_{ts}	10	50
Outer rotor diameter (mm)	D_{rc}	150	250
Stator slot height (mm)	h_{ss}	25	45
Ratio of the slot opening over the slot width	k_{open}	0.55	0.99

No initial solution is predicted in the design optimization study made with single and multi objectives. The optimization results were randomly generated by algorithms using the objective function. In the case of single objective operation, the motor efficiency, the total motor weight, the total weight of the magnets have been tried to be improved separately and the result graphs are shown in Figs. 4 and 5. In the case of multiobjective operation, the motor efficiency, the total motor weight, the total weight of the magnets have been tried to be mixed with fuzzy decision making and the membership result graphs are given in Fig. 6. Algorithm parameters such as population number are 100, iteration number is 100, crossover rate is 0.85 and mutual rate is 0.01 are taken the same in order to evaluate the optimization results correctly. When these graphs are examined, it can be said that genetic algorithm provides a good search and solution in single objective optimizations. In multiobjective optimizations, it can be stated that the fuzzy decision making and genetic algorithm provide a good fit and precise convergence. Furthermore, the selected population, iteration, crossover and mutation values are suitable.

Table 5 shows the optimal geometric results and Table 6 shows the optimal objective results, the optimal boundary results and the iteration numbers and times in which the optimal results were obtained. The values given in bold are the most appropriate results found. According to Table 5, a common observation in all iterations is the reduction of the rotor diameter, the increase of the magnet thickness and the increase of the stator slot height. The rotor diameter and slot height are interconnected. The PMSM needs sufficient magnet weight and winding area to provide the required torque. Table 6 emphasizes that results are obtained in accordance with each objective function and the boundary values are not exceeded. The situation that affects the iteration numbers and times is in particular the effectiveness of the genetic algorithm.

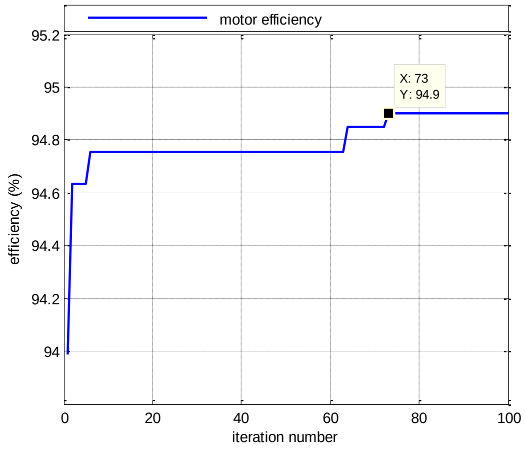

Figure 4. Optimal values of f_1 single objective function

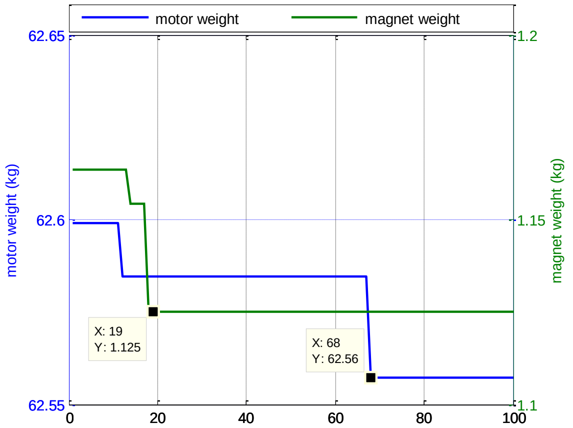

Figure 5. Optimal values of $f_2$and f_3 single objective functions

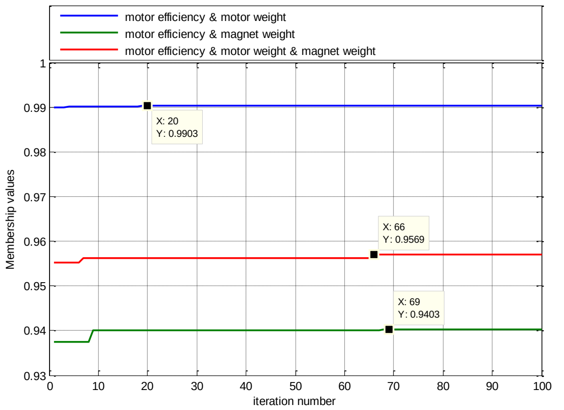

Figure 6. Convergence graphics of F_1, F_2 and F_3 multiobjectivefunctions

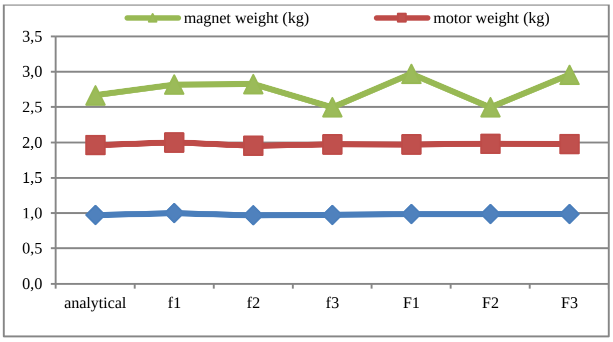

Figure 7. Sum of the scaled objective results

Fig. 7 shows linear curves showing the most appropriate solution for each row in Table 3. Each curve connects the points corresponding to sum of the scaled values of the three accepted objectives. According to Fig. 7, the motor efficiency and the motor weight are not changed sharply in the optimization, but the weight of the magnets sharply changes and affects the results. Linear curves emphasize that the weight of the magnets is a very effective objective function for the boundary values.

Table 5. Optimal geometric results

	D_{rc} (mm)	l_m (mm)	δ (mm)	h_{sw} (mm)	b_{ts} (mm)	h_{ss} (mm)	k_{open}
analytical	215	3.50	1.25	3.20	31.95	25.00	0.72803
f_1	165.54	5.20	1.41	1.75	27.28	44.90	0.86097
f_2	171.41	5.35	1.42	2.47	39.13	30.16	0.91731
f_3	155.18	3.58	1.16	1.86	36.51	42.13	0.83688
F_1	195.55	5.40	1.47	2.48	31.86	26.04	0.89151
F_2	150.49	3.62	1.41	1.97	25.99	43.89	0.97280
F_3	194.28	5.34	1.22	2.72	33.62	26.45	0.60763

The permanent magnet synchronous motor initially increased from analytical design to optimization, the motor efficiency increased from 92.33% to 94.9% while the total weight of the motor dropped from 62.83kg to 62.46kg and the total weight of the magnets dropped from 1.51kg to 1.1kg. While the improvement in motor efficiency is realized in the efficiency objective function (f1), the improvement in the total weight of the motor occurs in the efficiency-weight objective function (F1) and the improvement in the total weight of the magnets is in the efficiency-magnet objective function (F2). The most striking feature is the rate of change in the total weight of the magnets. If the results are generally evaluated in terms of constraint functions, the magnetic flux density does not increase so much as to cause saturation in any region on the motor sheet.

Table 6. Optimal objective and boundary geometric results, iteration numbers and times

	η (%)	$W_{tot}(kg)$	$W_{PMs}(kg)$	$B_{ry}(T)$	$B_{sy}(T)$	$B_{st}(T)$	Iter. number	Iter. time (s)
analytical	92.33	62.83	1.51	**0.27**	1.56	1.53	-	-
f_1	**94.90**	63.58	1.76	0.34	1.09	1.54	73	16.119
f_2	91.87	62.56	1.87	0.35	0.69	1.18	68	**14.277**
f_3	92.55	63.32	1.12	0.36	0.63	**1.08**	**18**	14.467
F_1	93.61	**62.46**	2.15	0.31	1.03	1.53	20	20.229
F_2	93.54	63.29	**1.10**	0.32	**0.53**	1.29	69	15.718
F_3	93.81	62.64	2.11	0.33	1.09	1.57	66	15.759

This is good news. A clear observation is that the thickness of the rotor yoke increases all the optimization results. It is seen from the values in Table 5, Table 6 and Fig. 7 that the most effective geometric parameter are permanent magnets. Results of the preliminary design and the F3 multiobjective optimization have been tested by means of a finite element program.

According to the finite element analyses, the input power of the motor is 2502.8W, the output power is 2251.6W, the efficiency is 89.96% and the torque is 86Nm for preliminary design. Also for the F3 fuzzy multiobjective design optimization, the input power of the motor is 2546.6W, the output power is 2366.9W, the efficiency is 92.94% and the moment is 90.4Nm. Efficiency error values are 2.63% and 0.94% for preliminary design and for the F3 fuzzy multiobjective design optimization respectively. In this case, the fuzzy multiobjective design optimization is confirmed with a low error and the design aims have been realized. In addition, the magnetic flux densities obtained by a finite element program are $B_{st} = 1.14\text{T}$, $B_{sy} = 1.42\text{T}$ and $B_{\text{ry}} = 0.85\text{T}$ for the analytical design and $B_{st} = 1.57\text{T}$, $B_{sy} = 1.28\text{T}$ and $B_{\text{ry}} = 1.14\text{T}$ for the F3 multiobjective design optimization. In this case, it can be said that the magnetic flux densities obtained as a result of the optimization are below the limit values and the multiobjective optimization modelling is useful.

Motor performance is evaluated in terms of operating performance; torque ripples of the PMSM are about 7.49% for preliminary design and 7.16% for the F3 fuzzy multiobjective design optimization on average, which is due to the magnet angle and stator winding. The cogging torque is effectively 1.1Nm for preliminary design which corresponds to 1.28% of the nominal torque and 1.3Nm for the F3 fuzzy multiobjective design optimization which corresponds to 1.44% of the nominal torque. The choice of the slot number and the number of poles is influential in the formation of this value. As a result, PMSM design optimization with a very complex and non-linear structure has been tried to be solved with a different approach such as fuzzy-genetic. Taking into account the obtained optimization values, the finite element results and the iteration times, the fuzzy-genetic approach is quite useful for PMSM design and the designed PMSM provides the desired performance with great precision.

5. Conclusion

In this study, design optimization of the permanent magnet synchronous motor, which is frequently used in low speed high torque applications, was realized by using fuzzy decision making and genetic algorithm. Motor efficiency, motor weight and weight of magnets were selected as the single objective functions and to form multiobjective the single objective functions are combined with the fuzzy decision process. Here the goal was to achieve any single objective while other objectives were to achieve the desired values.

Convergence curves of algorithms show performance. It can be argued that ability of the genetic algorithm to fall locally has been overcome by the fuzzy decision making process, which seems to be promising. Sensitive values in the obtained design parameters also demonstrate the ability of the algorithms to investigate. The most successful aspect of the multiobjective algorithm is to provide a highly flexible approach to the goals. It can be seen that both results, fuzzy multiobjective optimization and finite element program are very close to each other and the error margin can be deducted from the evaluation.

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