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Efficiency Improvement of Axial Flux PM Motor Using Particle Swarm Optimisation

***Abstract**. In this paper a particle swarm based optimal design of axial field permanent magnet motor (AFPMM) is proposed. This approach employs a particle-swarm-optimization (PSO) technique to search for optimal design solution of an AFPMM based on the efficiency value of the motor. A comparative analysis of the optimised solution and the prototype is presented and it is based on the values of the optimised objective function, on the values of the optimisation parameters, and on a set of electric and magnetic parameters of the motor.*

***Streszczenie.** W artykule opisano wykorzystanie metody optymalizacji roju cząstek w projektowaniu maszyny synchronicznej z magnesami trwałymi o strumieniu osiowym (ang. AFPMM). Dokonano analizy porównawczej wyznaczonych optymalizacji oraz przedstawiono prototyp oparty na wartościach parametrów optymalizacji oraz parametrach elektrycznych i magnetycznych maszyny. (**Wykorzystanie metody optymalizacji roju cząstek w zwiększeniu sprawności maszyny AF-PMSM**).*

Keywords: Efficiency, axial flux permanent magnet motor, particle swarm optimisation.
Słowa kluczowe: sprawność, silnik synchroniczny z magnesami trwałymi o strumieniu osiowym, optymalizacja roju cząstek.

Introduction

Interest in means of optimisation of electric machine design is high because of increased cost of electrical energy, plus the increased competition in world markets. The objective of the optimisation process is usually to minimise the cost of the machine or to maximise the efficiency of the machine. This work in this paper will be focused on the optimisation of the motor design using efficiency as an objective function.

The design of a machine can be described by a vector *X* of *n* variables stating dimensions or dimension ratios, current densities, flux densities etc. The design is subject to a set of *m* constraints which may include specifications arising from thermal, mechanical, electrical, magnetic, manufacturing or dimensional limits. The goal of the optimal design is to make the chosen objective function *F*(*X*) to reach its optimum value while keeping other technical indices within acceptable ranges. The complexity of electric machine design is such that explicit methods of optimisation such as those dependent on making certain derivatives equal to zero are not feasible. Thus most practical optimisation employs nonlinear programming methods.

Description of Particle Swarm Optimisation Method

This stochastic optimisation method has been recently proposed and introduced as an optimisation tool [1-3]. PSO is based on the analogy of swarm, as flock of birds or school of fish. PSO mimics the behaviour of individuals in a swarm to maximise the survival of the species. In PSO, each individual makes its decision using own experience together with other individuals' experiences. The algorithm, which is based on a metaphor of social interaction, searches a space by adjusting the trajectories of moving points in a multi-dimensional space. The individual particles are drawn stochastically toward the position of present velocity of each individual, their own previous best performance, and the best previous performance of their neighbours. The main advantages of PSO algorithm are summarised as simple concept, easy implementation, robustness to control parameters, and computational efficiency when compared with deterministic methods and other stochastic optimisation techniques. Unlike the other heuristic techniques, PSO has a flexible and well balanced mechanism to enhance and adapt both to the global and local exploration abilities.

Similar to evolutionary algorithms, the PSO technique conducts searches using a population of particles, corresponding to individuals. Each particle represents a candidate solution to the problem at hand. In a PSO stem, particles change their positions by flying around in a multidimensional search space until a relatively unchanged position has been encountered, or until computational limitations are exceeded. In social science context, a PSO system combines a social-only model and a cognition-only model. The social-only component suggests that individuals ignore their own experience and adjust their behaviour according to the successful beliefs of individuals in the neighbourhood. On the other hand, the cognition-only component treats individuals as isolated beings. A particle changes its position using these models. The advantages of PSO over other traditional optimisation techniques can be summarized as follows:

a. PSO is a population-based search algorithm (i.e., PSO has implicit parallelism). This property ensures PSO search not to get trapped on local minima.
b. PSO uses payoff (performance index or objective function) information to guide the search in the problem space. Therefore, PSO can easily deal with non differentiable objective functions. Additionally, this property relieves PSO of assumptions and approximations, which are often required by traditional optimization methods.
c. PSO uses probabilistic transition rules and not deterministic rules. Hence, PSO is a kind of stochastic optimization algorithm that can search a complicated and uncertain area. This makes PSO more flexible and robust than conventional methods.
d. Unlike GA and other heuristic algorithms, PSO has the flexibility to control the balance between the global and local exploration of the search space. This unique feature of PSO overcomes the premature convergence problem and enhances the search capability.
e. Unlike the traditional methods, the solution quality of the proposed approach does not rely on the initial population. Starting anywhere in the search space, the algorithm ensures the convergence to the optimal solution.

The basic elements of PSO technique are briefly stated and defined as follows:

- *Particle X*(*t*): It is a candidate solution represented by an *m*-dimensional real-valued vector, where *m* is the number of optimised parameters. At time *t* the *j*-th particle can be described as $X_j(t)= [x_{j,1}(t), x_{j,2}(t),... x_{j,m}(t)]$; here 'x' are the optimised parameters, and $x_{j,k}(t)$ is the position of the particle with respect to the *k*-th dimension (i.e., the value of the *k*-th optimised parameter in the *j*-th candidate solution).

- *Population pop*(*t*): It is a set of *n* particles at time *t* (i.e., $pop(t)=[X_1(t), X_2(t),\ldots X_n(t)]^T$).
- *Swarm*: It is an apparently disorganised population of moving particles that tend to cluster together while each particle seems to be moving in a random direction.
- *Particle Velocity V*(*t*): It is the velocity of the moving particles represented by an m-dimensional real valued vector.
- *Weighting Function w*(*t*): It is a control parameter that is used to control the impact of the previous velocities on the current velocity. Hence, it influences the trade-off between the global and local exploration abilities of the particles.
- *Individual Best* X*(*t*): As a particle moves through the search space, it compares its fitness value at the current position to the best fitness value it has ever attained at any time up to the current time. The best position that is associated with the best fitness encountered so far is called the individual best X*(*t*).
- *Global Best* X**(*t*): It is the best position among all of the individual best positions achieved so far.
- *Stopping Criteria*: These are the conditions under which the search process will terminate. In this study, the search will terminate if the number of iterations reaches the maximum predefined number.

The considered values of the basic PSO parameters for this optimal design problem are presented in Table 1.

Table 1. Values of the PSO parameters

PSO parameters	Value
Population size	10
Number of particles	7
Number of iterations	500

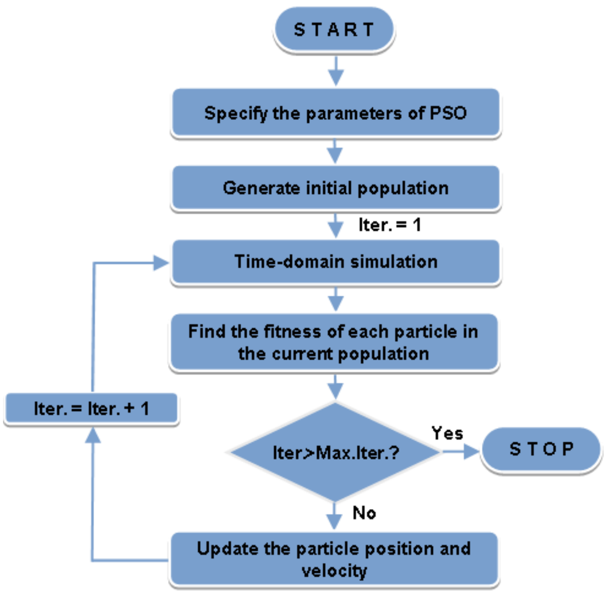

Fig.1. PSO block diagram of the PS-ODEM programme

Implementation of PSO in Optimal Design of AFPMM

The general aim of the axial flux permanent magnet motor (AFPMM) optimal design is to obtain a motor with increased efficiency while satisfying certain performance, magnetic and geometric constraints. The design optimisation, using the programme PS-ODEM (Particle Swarm for Optimal Design of Electrical Machines), is performed on a prototype axial flux permanent magnet motor with rated torque 54 Nm and speed 750 rpm. The investigated motor is a double sided axial field motor with two laminated stators having 36 slots and a centred rotor having 8 skewed neodymium-iron-boron permanent magnets with B_r=1.17 T and H_c=-883 kA/m. A side view of the prototype motor is shown in Fig. 2. In this solution the two stators are attached to the chassis of the vehicle, where the rotor is fixed to the shaft of the wheel and free to move in a vertical direction. The rotor of this machine has to be carefully constructed so that it has adequate mechanical integrity and with less weight as possible. The weight of the rotor in such a solution is increasing the unsprung mass of the vehicle, but it is far less than the mass of the whole motor as in some other suggested solutions.

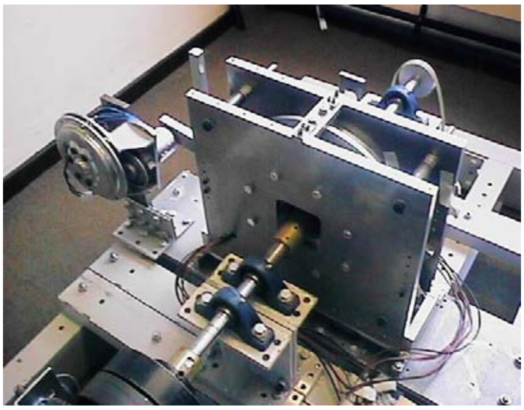
Fig.2. Axial flux PM motor prototype view

As previously mentioned the efficiency of the motor is selected as an objective function of the optimisation, since the energy saving is especially important in the application of the AFPMM for electric vehicle (EV) drive. According to the design characteristics of the designed by hand prototype AFPMM, some of the parameters are chosen to be constant and some variable, such as: inside radius of the PM and the stator core $\boldsymbol{R_i}$, outside radius of the PM and of the stator core $\boldsymbol{R_o}$, permanent magnet fraction $\boldsymbol{\alpha_m}$, permanent magnet axial length $\boldsymbol{l_m}$, air-gap $\boldsymbol{g}$, single wire diameter $\boldsymbol{d_w}$ and sloth width $\boldsymbol{b_s}$. The objective function for the optimisation is presented by equations (1).

$$efficiency = \eta = \frac{T \cdot \omega_m}{T \cdot \omega_m + P_{Cu} + P_{Fe} + P_s} \tag{1}$$

where: T -rated torque, ω_m -rated speed, P_{Cu} -ohmic power loss, P_{Fe} -core power loss and P_s -other constant losses.

Table 2. PSO parameter optimisation bounds

Parameters	Lower bound	Upper bound	Prototype
R_i [m]	0.070	0.074	0.072
R_o [m]	0.128	0.138	0.133
α_m [/]	0.6	0.730	0.6646
l_m [m]	0.009	0.011	0.010
g [m]	0.0018	0.0022	0.002
d_w [m]	0.0008	0.0014	0.001
b_s [m]	0.0070	0.0090	0.008

The stopping rule while the particle swarm optimisation works is selected to be the number of iterations. The lower and upper bound, and the optimisation parameters values of the prototype model, are presented in Table 2. The comparative optimisation parameters data of the basic and optimised model are presented in Table 3. The convergence of the efficiency of the motor as an objective function during the particle swarm optimisation search for 500 iterations is shown in Fig. 3.

Table 3. PSO results

Variable	Unit	Prototype	PSO solution
R_i	(m)	0.072	0.074
R_o	(m)	0.133	0.1345
α_m	(/)	0.6646	0.73
l_m	*(m)*	0.010	0.011
g	(m)	0.002	0.00214
d_w	(m)	0.001	0.0014
b_s	(m)	0.008	0.009
Efficiency	(/)	0.8319	0.8562

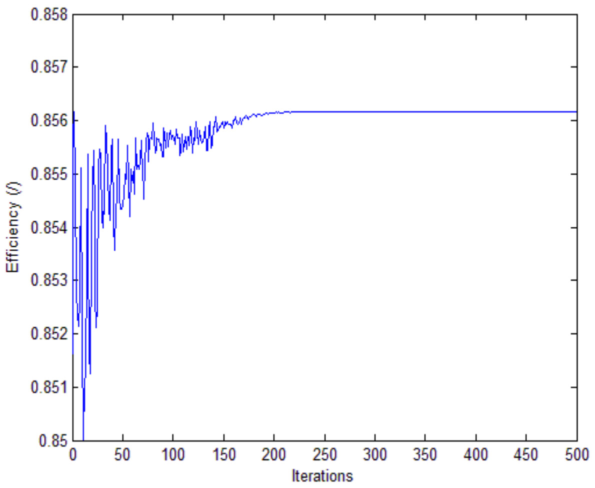

Fig. 3. Efficiency change during PSO search

For comparison analysis the values of some specific parameters for the PSO solution and for the prototype model are shown in Table 4. These values show evident improvement of the presented parameters and characteristics of the optimised AFPMM model in relation to the prototype. It is evident that the PSO solution in relation to the prototype has less total weight and a bit smaller efficiency, which is due to the increase of the resistance of the winding per phase. The decrease of the permanent magnets overall weight of the optimised model in relation to the prototype could lead to a reduction of the prise of the motor. This improvement in the PM weight, as well as the weight of the rotor iron could also lead to an improvement of the performance of the EV since the rotor is directly mounted on the shaft of the vehicle.

Table 4. PSO comparative results

Parameter	Unit	Prototype	PSO solution
Efficiency	(/)	0.8319	0.8562
I_{ph}	(A)	8.723	8.7304
R_{ph}	(Ω)	1.245	0.707
P_{Cu}	(W)	345.43	196.53
P_{Fe}	(W)	15.03	19.36
B_g	(T)	0.695	0.728
W_s	(turns)	13	12
$V_{s\ teeth}$	(m^3)	0.000674	0.000948
$V_{s\ back\ iron}$	(m^3)	0.001067	0.0012
V_{pm}	(m^3)	0.0005018	0.0003182

AFPMM Modelling for FEM Analysis

The quasi 3D method which is adopted for this analysis [4] consists of a 2D FEM calculation of the magnetic field in a three dimensional radial domain of the axial field motor. For this purpose, a notional radial cut through the two stators and one rotor of the disc motor is performed and then opened out into linear form, as shown in Fig.4 and Fig. 5. By using this linear quasi three dimensional model of the AFPMM, which is divided into five segments, as presented in Fig.5, it is possible to model the skewing of the permanent magnets and also to simulate the vertical displacement and rotation of the rotor.

Due to the symmetry of the machine the calculation of the motor is performed only for one quarter of the AFPMM or for one pair of permanent magnets.

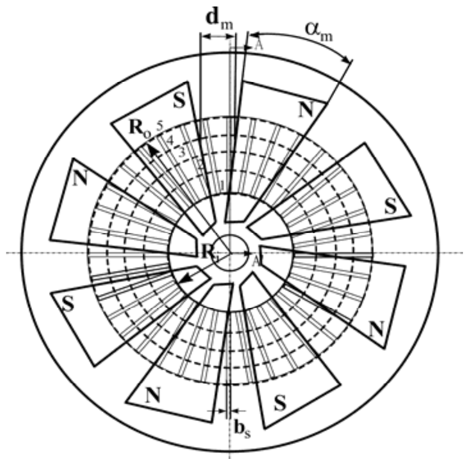

Fig. 4. Radial division of the motor into 5 segments

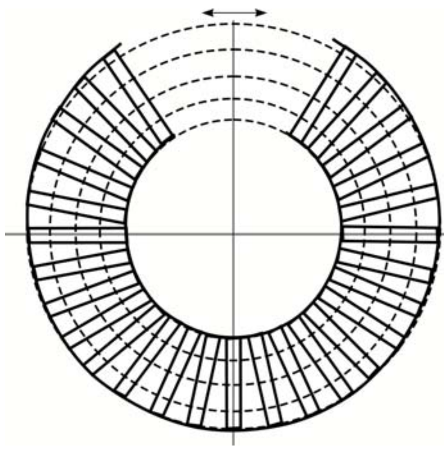

Fig. 5. Radial cut of the motor

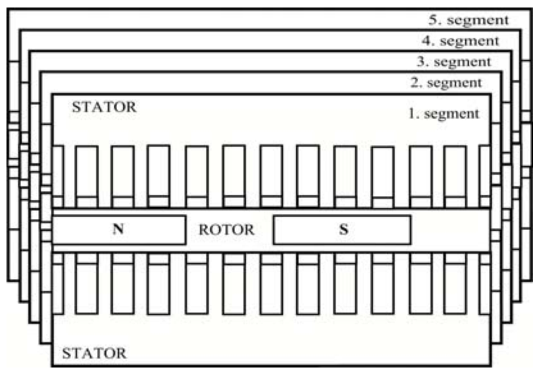

Fig. 6. Linear presentation of the motor

Magnetic Field Calculation

After the axial flux permanent magnet motor has been properly modeled, in the processor mode a quasi-3D FEM magnetic field calculation [4] of the motor for each segment separately at no load and at rated current load for both models is performed. The magnetic field calculation for different rotor positions at different loads is also performed. Here, as an example the distribution of the magnetic field for the AFPMM for the middle segments of both models at no load is presented in Fig. 7 and Fig. 8, respectively.

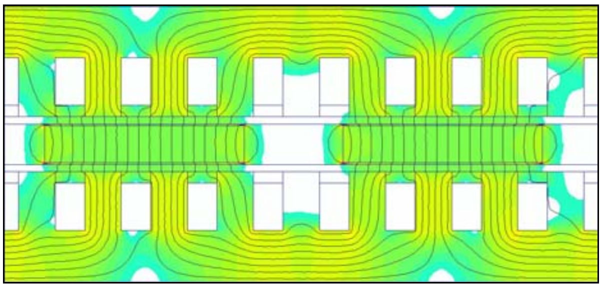

Fig. 7. Magnetic field distribution at no load for the prototype

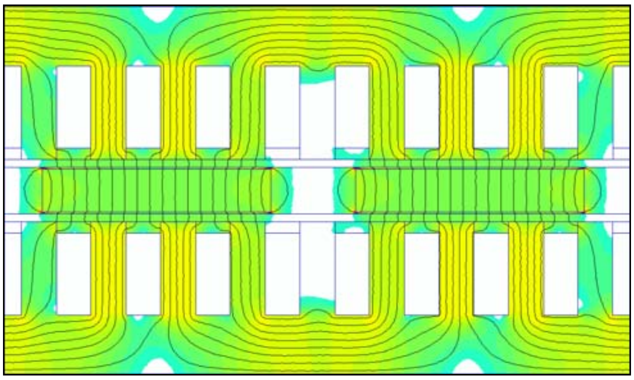

Fig. 8. Magnetic field distribution at no load for the PSO model

In the postprocessor mode of the program [5] using the data from the magnetic field calculation, the value of the air gap flux density in the middle of the air gap can be calculated by using equation (2) and solving it numerically.

$$\mathbf{B} = \operatorname{curl} \mathbf{A} \tag{2}$$

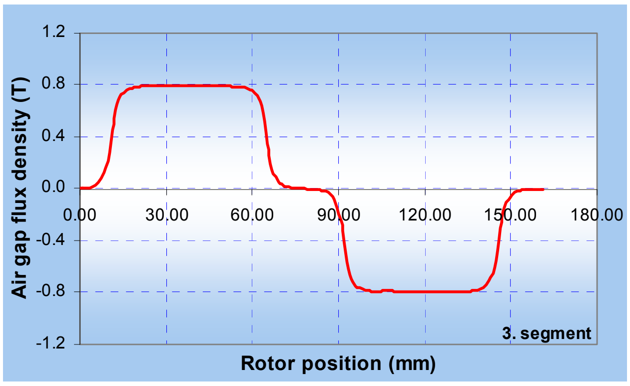

Fig. 9. Air gap flux density distribution at no load for the prototype

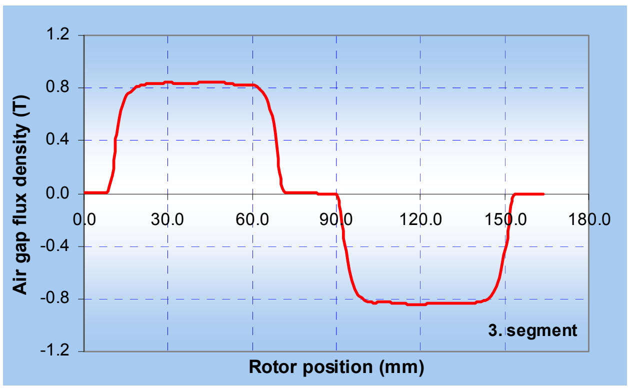

Fig. 10. Air gap flux density distribution at no load for the PSO model

The value of the air gap flux density for the axial field permanent magnet synchronous motor is calculated for different current loads and for all five segments. Due to lack of space the distribution of the air gap flux density is only presented for the middle segment of the AFPMM models at no load for both models in Fig. 9 and Fig. 10, respectively.

Magnetic Field Calculation

An optimisation technique based on particle swarm optimisation has been developed and applied to the design of an axial flux permanent magnet motor. According to the results investigated above, it can be concluded that the PSO is a very suitable tool for design optimisation of AFPMM and electromagnetic devices in general. By using PSO the risk of trapping in a local maximum or minimum is extremely reduced, which is very difficult to eliminate in deterministic methods. At the end the quality of the PSO model has been proved through the data analysis of the prototype and optimised solution. This improvement resulted in energy efficiency improvement of the motor which is very important for the improvement of the EV performance. At the end, the quality of the PSO solution has been proved by comparative analysis of the two motor models using Finite Element Method as a performance analysis tool. The proper modelling of the AFPMM is presented and partial comparative results of the magnetic field and air gap flux density distribution for no load are presented.

For future work a proper performance analysis, including electromagnetic torque and cogging torque analysis, for both models is going to be performed in order to take into account of all aspects of the motor working characteristics.

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