PREFERENCE BASED AND IDEAL MULTI-OBJECTIVE OPTIMIZATION APPLIED ON HIGH-TORQUE FERRITE ASSISTED SYNCHRONOUS RELUCTANCE MACHINE

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Abstract: This paper introduces comparison of optimization algorithms applied on high-torque ferrite-assisted synchronous reluctance machine. The comparison is focused not solely on two algorithms within the same multi-objective optimization approach - preference based or ideal, but also on comparison of these two approaches. The genetic algorithm and self-organizing migrating algorithm in both approaches are used to find optimal solution. The optimization goal is an optimal parameter combination to achieve the highest torque and power factor, while developing the lowest torque ripple. The optimized design will be evaluated by the 2D finite element analysis in steady-state analysis.

Keywords: steady-state, synchronous reluctance motor, finite element analysis, optimization

1 INTRODUCTION

The synchronous motor (SM) branch development has taken a big leap during the last 30 years [1], mainly due to discovery of rare-earth magnets - either neodymium-iron-boron or samarium-cobalt compounds, but also due to the pressure put on efficiency in area of electric motors (EM) (new more strict European standards - IEx). Nowadays, the situation in the SM development has reached a point, where the SMs are working with superior efficiency over other drive types, but also due to the increased permanent magnet (PM) prices the PM-assisted SMs have become expensive solutions.

The low-cost SMs have thus become attractive research topic aiming to develop cheaper SM competitor to low-cost induction machines. The low-cost machines suitable for traction applications, the topic of this paper, taking cost effective point of view into account are synchronous reluctance machines, while only PM-assisted synchronous reluctance machines are usually considered due to the higher torque, thus higher power density ratio. The price of the PMs is affected by multiple factors, the main being the geopolitical factor, majority of rare-earth ores is located in a few countries. Therefore, the solution of this price reduction approach lays in a use of cheaper PM material - ferrite magnet. The price of ferrites seems to be not affected by the price fluctuations of other PM ores and its cost remains just a portion of rare-earth competitors.

The topology choice, regardless of its undisputed importance is just a starting point of the whole design process. The next step in the machine design process is to provide reasonably chosen set of geometry parameters and their optimal values. The simplest way of optimization could be performed by trial and error approach - parametric analyses or manual testing. The optimal design could be found also by optimization algorithms (OA), which is commonly used technique resulting usually in better and efficiently found solutions. The commonly used algorithms in EM optimization design are the evolutionary algorithms. The best known algorithm in this group is the genetic algorithm (GA), that is found in many variations and also in both preference based and ideal multi-objective optimization (MOO) versions. The other OA that is considered in this paper, that is also found in

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both MOO variations is self-organizing migrating algorithm (SOMA).

This paper considers high-torque ferrite-assisted synchronous reluctance (FASR) machine used in ship propulsion application for an MOO algorithm comparison using three objectives as an aim for optimization. These objectives, that are evaluated by 2D finite element analysis, are as follows - electromagnetic torque, torque ripple and power factor.

2 OPTIMIZED MACHINE

The investigated machine is the FASR machine has ten poles and is equipped with the integral slot winding distributed in 60 slots. The machine dimensions are listed in Table 1 and the parametric geometry is depicted in Figure 1. The optimized machine has three flux barriers, that was found optimal for this machine type within the limited machine dimensions.

Parameter	Symbol	Value
Rated output torque	T_N	3100 Nm
Rated speed	n	150 min^{-1}
Stator out. diam.	D_{out}	584 mm
Stator inner diameter	D_{in}	470 mm
Stack length	L_{stk}	306 mm

Table 1: Key machine parameters

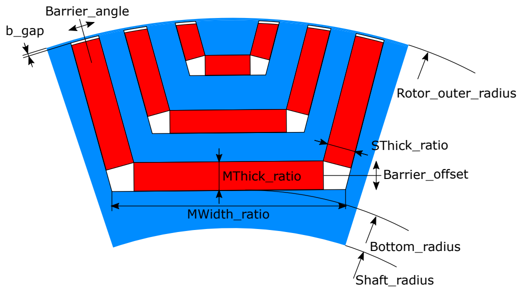

Figure 1: Parametric optimized geometry

The parameters MThick_ratio and SThick_ratio are related to the rotor space volume. A barrier width parameterized by the MWidth_ratio is related to the pole-width. Other parameters are used to distort the equidistant barrier placement Barrier_offset or barrier end angle Barrier_angle. Both outer and inner rotor radius defined Rotor_outer_radius, Shaft_radius respectively are fixed during the optimization. The bridge between the barrier end and air gap b_gap is fixed as well to 0.5 mm. The number of optimized parameters is therefore 15 (5 parameters for each barrier) plus parameter Bottom_radius defining the bottom barrier placement.

3 OPTIMIZATION ALGORITHMS

The OA is according to [2] is a programmable process or function, that takes some sort of input parameter or value that modify characteristics of the device or function to find the minimum or maximum value of a result or a output. The evolutionary algorithms works on repeating certain algorithm procedures, when each repeated procedures combination, i.e. generation in GA or migration in SOMA, starts where the previous ended. By this repetition is supposed to find better design each iteration and therefore ideally result in an globally (best result in a investigated space) optimal solution. The preference based MOO (PB-MOO) works on a principle of combining the normalized (dimensionless) objective values with their weight factors, increasing or decreasing aim of the optimization into single value, which is then minimized. To this combination of weight coefficients and normalized objectives is usually referred to as a “Cost function” or a “Fitness function”. Algorithms working on this principle are usually less sophisticated and less efficient in the global optimum search. The ideal MOO (I-MOO) is on the other hand programmed to optimize the objectives equally, without influencing the algorithm objectives aims. This kind of algorithm is easier to initialize, since no weight coefficients nor desired values are required. I-MOO algorithms are more sophisticated and the result of optimization is easier to interpret, since each individual carries direct objective information not only cost function value. Also instead of single optimal solution, whole set of optimal solutions is delivered, this set is called Pareto optimal set of solutions.

3.1 GENETIC ALGORITHM

This algorithm is based on the Darwinian theory of evolution. The principle is based on combination of following principles - survival of the fittest, reproduction and the occasional positive mutation [2]. The repetition of these procedures ideally results in a optimal solutions. The whole process of GA is depicted in Figure 2(a). The I-MOO is following the same principle, but instead of sorting the population based solely on the cost function are the individuals sorted by non-dominant sorting process. This procedure is sorting individuals in Pareto fronts. In each front are individuals, where improvement of one objective leads to a decay of a second or other objective and also according to the distance between the solutions within the same Pareto set. Many I-MOO versions of GA were applied in EM design, but the most popular version, that is also used in this paper, is non dominated sorting genetic algorithm (NSGA-II).

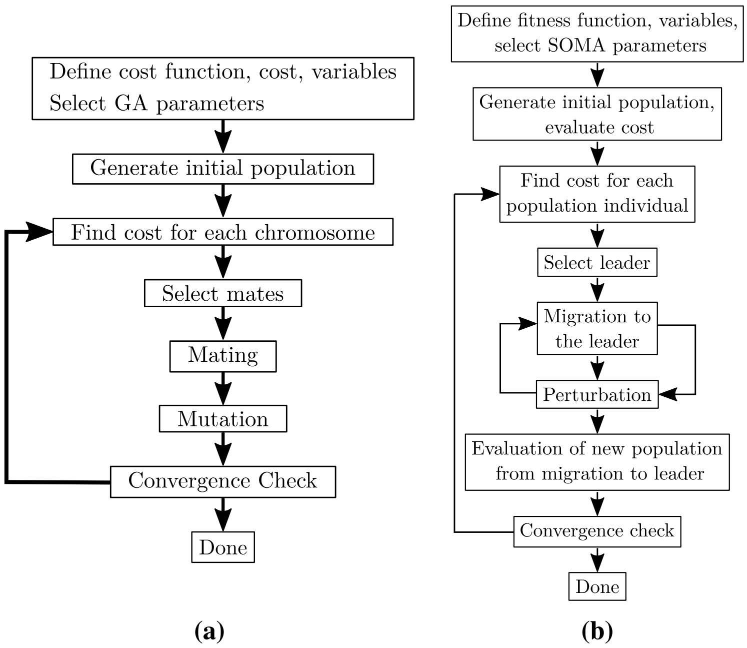

Figure 2: (a) Principle of GA (b) Principle of SOMA

3.2 SELF-ORGANIZING MIGRATING ALGORITHM

The principle of SOMA is based on the predator-prey situation, where is a herd of predators searching for a prey in a specific area. The original author is in [3] presenting the behavior on a pack of wolves searching for a food. An assumption is, that one member of predator herd is always closest to the prey, the member becomes a herd leader, and other members are traveling toward him. Seldom occur a situation, where one predator become even closer to the prey comparing to the original leader and other members changes traveling trajectories toward the new leader. This procedure, called migration, is repeated multiple times until the prey is found. The prey is in optimization terminology representing the global optimum and the herd of predators is the optimized population. In PB-MOO the global solution has the lowest cost function value. In I-MOO is the "prey" represented by the Pareto set of optimal solutions toward the population is migrating to. The SOMA principle is depicted in 2(b).

3.3 OPTIMIZED PARAMETER RANGES AND ALGORITHMS SETTING

The geom. parameters defined are varied during the optimization within the ranges listed in Table 3. The optimization algorithms have specific set of parameters that allow the user to influence the optimization processes. All the parameter values in Table 4 are chosen based on OA founders recom-

Parameter	Flux-barrier 1	Flux-barrier 2	Flux-barrier 3
MWidth_ratio, -	$0.2 \div 0.85$	$0.2 \div 0.85$	$0.2 \div 0.85$
MThick_ratio, -	$0.2 \div 0.85$	$0.2 \div 0.85$	$0.2 \div 0.85$
SThick_ratio, -	$0.2 \div 0.85$	$0.2 \div 0.85$	$0.2 \div 0.85$
Barrier_offset, (mm)	$-2 \div 2$	$-2 \div 2$	$-2 \div 2$
Barrier_angle, (deg)	$10 \div 22$	$-3 \div 3$	$-3 \div 3$
Bottom_radius, (mm)	$165 \div 180$		

Table 3: Boundaries of the optimized parameters.

mended values or the authors good experience in EM optimization. The common parameter across the algorithm is the fitness function evaluation (FFE), that set the same boundaries in terms of algorithm time demands to all OA. Therefore 20,000 FFE evaluations were supposed to be done by each OA. Weight coefficients in both PB-MOO algorithms were chosen to equally optimize all objectives.

OA/Parameter	SOMA	MOSOMA
Initial population	50	50
Mig. agents (SOMA-all)	-	15
Number of mig. steps	20	10
Mig. path length	2.1	1.7
Perturbation	0.3	0.1

OA/Parameter	GA	NSGA-II
Initial population	50	50
Crossover	3	0.5
Mutation rate	0.2	0.2

Table 4: OA parameters initialization

4 OPTIMIZATION RESULTS

The optimized results from PB-MOO are depicted as a development of the cost function value over the individual count, whereas the I-MOO algorithms figure depict distributed solutions in the objective space. Optimal solutions are highliged in all figures with the corresponding objectives value.

All algorithms except the SOMA algorithm evaluated 20,000 FFE, the SOMA algorithm met the convergence criteria sooner, therefore the algorithm finished. The results clearly shows the advantage of the I-MOO optimization procedures over PB-MOO approach. Both I-MOO algorithms sufficiently found solutions, that meet the desired objectives listed in Table 1, while the NSGA-II algorithm delivers evenly distributed solutions on and between the Pareto fronts. The PB-MOO algorithms failed to find a optimal solution in this application, the reason could be the high number of optimized parameters, that favors the I-MOO solvers. Chosen NSGA-II optimized result (highlighted by a star in Figure 3(d)) flux-density surface plot is depicted in Figure 4.

5 CONCLUSION

This article presents the comparison of four optimization algorithms in both I-MOO and PB-MOO approaches applied to the ferrite-assisted synchronous reluctance machine. The selected OAs that exist in both versions are GA and SOMA. The I-MOO approach of both algorithms resulted to be superior over their PB-MOO counterparts, while GA in both MOO approaches dominated over SOMA. This could be caused by relatively high amount of optimized parameters within the decision space. The optimization goal was reached by both I-MOO algorithms with higher torque ripple in case MOSOMA.

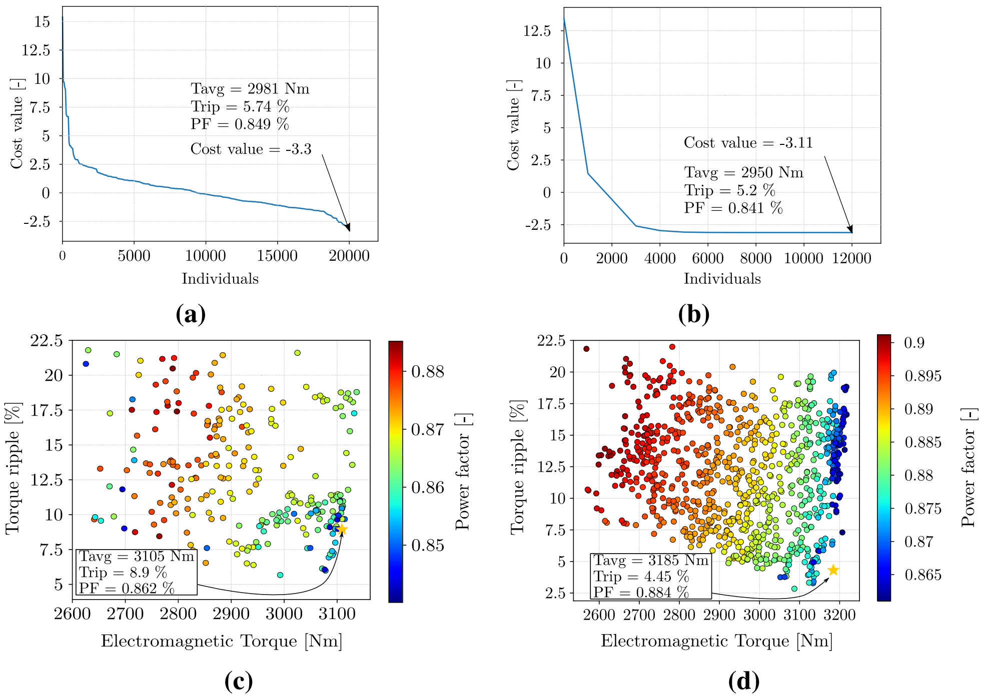

Figure 3: a) Principle of GA b) Population sorting in I-MOO version of GA

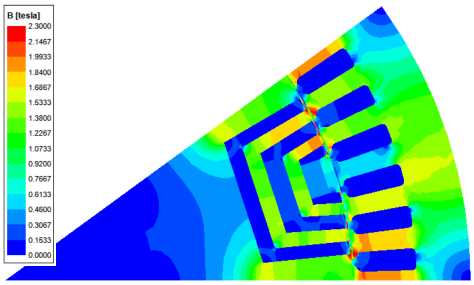

Figure 4: Flux-density surface plot in optimized machine

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