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# Using Interactive Multiobjective Optimization to Design a Permanent Magnet Synchronous Generator

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## Abstract

We consider an analytical model of a permanent magnet synchronous generator and formulate a mixed-integer constrained multiobjective optimization problem with six objective functions. We demonstrate the usefulness of solving such a problem by applying an interactive multiobjective optimization method called NIMBUS. In the NIMBUS method, a decision is iteratively involved in the optimization process and directs the solution process in order to find her/his most preferred Pareto optimal solution for the problem. We also employ a commonly used noninteractive evolutionary multiobjective optimization method NSGA-II to generate a set of solutions that approximates the Pareto set and demonstrate the advantages of using an interactive method. This study is the first one to consider an interactive approach for the design of a permanent magnet synchronous generator. Thus, we promote the further usage of interactive multiobjective optimization methods in the design. Further, we see that these methods could also be very useful in the teaching of electrical machines.

## 1 Introduction

Permanent magnet synchronous generators (PMSGs) are typically used for example in wind power systems, because they have a high efficiency and energy yield. No additional power supply is needed for the magnetic field excitation, because it is created by the permanent magnets (PMs). Due to the absence of the excitation winding in the rotor, rotor losses are reduced, improving also the thermal characteristics of the generator [LC08].

For a wind power turbine system, the following criteria are important: reliability and ease of maintenance, total mass of the nacelle, cost and energy yield and grid integration issues [TABD12]. The reliability can be greatly improved by choosing a direct-drive generator system, where the generator is directly connected to the hub, and a gearbox is not needed. However, this means that the rotation speed of the generator is low, which in turn means that a high torque is required, thus, leading to a larger size of generators [LC08]. Consequently, mass minimization becomes an important part of the generator design.

The cost of the generator is a non-negligible part of the wind power system. According to [Dub04], the cost of the generator of a 1.5 MW direct-drive wind turbine system was 36% of the total cost. The price of the rare earth magnets has been changing quite a lot during the past 10 years. A reason for this is that almost 95% of rare earth materials are mined in China and the prices vary according to the needs of the Chinese industry [TABD12]. When it comes to the energy yield and grid integration, the direct-drive PMSG is the best choice, because of its high efficiency and fault tolerance [TABD12]. The grid integration is mainly taken care of by the power electronics converter (which is not in the scope of this work). The size of the converter naturally depends on the characteristics of the PMSG, particularly, on its power factor.

There are several different PM machine topologies that can be used in wind power generators. In this paper, we focus on the radial flux surface mounted PMSG for the following reasons. First, it has a good performance over a wide range of speeds. Secondly, surface mounted magnet rotors are simple to manufacture. According to [Gra96], radial flux generators can be slightly more efficient and need slightly less active material than axial flux generators do. In [Dub04], optimized radial-flux machine designs had lower costs and masses than optimized axial flux designs for a given average nominal torque.

Designing any electrical machine involves coping with several conflicting objectives. Therefore, there arises a need for multiobjective optimization. Multiobjective optimization problems usually have several optimal solutions called Pareto optimal solutions with different trade-offs among the objectives. Often, a decision maker (DM) who is an expert in the domain of the problem is involved and provides her/his preference information to choose one among several possible Pareto optimal solutions for implementation. There are different multiobjective optimization methods to support the DM to find her/his preferred solution, see e.g., [Mie99, BDMSe08].

In PMSGs, the most typical optimization objectives are to minimize the cost [DJT16, VSD10, BCW15, ERN15], to maximize energy yield [DJT16, BCW15], to maximize the efficiency [TA14, VSD10], to minimize the mass [PK15, BVB08], to maximize the power density [TA14], or to maximize the power factor of the generator [BVB08]. However, in the literature, typically only one [PK15, ERN15, VSD10] or two objectives [TA14, BVB08, DJT16] are optimized at the same time. Often, when there are multiple objectives, a weighted sum of the objective functions is applied, thus, forming a single objective optimization problem [BCW15, VZI06].

Typically, global optimization techniques are required for electrical machines. During the past years, genetic algorithms (GA) have been used e.g. in [TA14, ERN15, VSD10], sequential quadratic programming algorithms in [BVB08, BCW15], and particle swarm optimization (PSO) in [DJT16, ERN15]. In [ERN15] both GA and PSO were combined with a gradient based solver to produce two hybrid solvers. In [VSD10], GA was used with an analytical model to find the global optimum, and after that, a constrained nonlinear optimization algorithm was used with a finite element model to improve the obtained solution even further. In [DI13], a comparative benchmark study was done between response surface (RS) and differential evolution (DE) algorithms in multiobjective optimization of a surface mounted permanent magnet synchronous machine. The optimization process had two objectives, a weight function, which was a combination of the total mass and the PM mass, and a goodness function, which took into account the torque and power losses. The result showed the DE algorithms to be superior over the RS methods.

Studies involving multiobjective optimization in the design of permanent magnet synchronous machine reveal that often *a)* the number of design objectives is limited to at most three, *b)* a weighted sum is often considered where the DM provides her/his preference information a priori, *c)* evolutionary multiobjective optimization algorithms are used to generate a representative set of Pareto optimal solutions, and *d)* no support is given for the DM to learn about the problem considered and find her/his preferred Pareto optimal solution. At this point we wish to emphasize that unlike the usual practice of considering up to three objectives in the design optimization problems, it is important to consider all the necessary objectives that define the problem. This is because the DM must understand the trade-offs between all relevant objectives to ultimately obtain a practically usable preferred Pareto optimal solution. We suspect that the main reason for the restriction on the number of objectives considered in the literature is the limited knowledge of methods available to solve multiobjective optimization problems.

On one hand, even though the weighted sum of objectives is simple to use, it has several deficiencies [Mie99] such as it cannot generate all Pareto optimal solutions when the optimization problem has nonconvex functions and bigger weights do not necessarily imply higher importance to objectives.

One way to alleviate some of the problems with the currently used methods in the design of is to use an interactive multiobjective optimization method. In a typical interactive method, the DM iteratively directs the solution process towards her/his preferred Pareto optimal solution by investigating a small subset of Pareto optimal solutions during every iteration. In each iteration, the preference information provided by the DM is used to formulate single objective optimization subproblem(s), which is/are solved to yield Pareto optimal solution(s) reflecting the preferences. Among interactive methods, the synchronous NIMBUS method [MM06] has been used to find preferred Pareto optimal solutions in several industrial problems, e.g., in [HMN06] and [HMS11]. The main advantages of using the synchronous NIMBUS method are that *a)* it can generate any

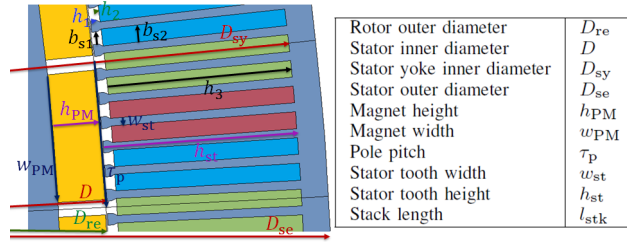


Figure 1: An example of a PMSG cross-section and the main geometrical parameters of the PMSG model.

Pareto optimal solution, *b*) it introduces only a low cognitive load on the DM as only a maximum of four solutions are shown to the DM at a time (and the DM can specify the number), *c*) it has a low computational overhead as only solutions desirable to the DM are generated, and *d*) it provides decision support to the DM when using the IND-NIMBUS software (implementing the method) to learn about the trade-offs among the objectives.

Evolutionary multiobjective optimization (EMO) methods have been used in designing PMSGs. They aim at finding a well distributed set of solutions that are as close as possible to Pareto optimal solutions. When using this well distributed set of solutions, the DM often encounters a laborious task of choosing her/his preferred solution with limited support. Furthermore, EMO methods face significant challenges with a large number of objectives such as a slow rate of convergence, the requirement of a large number of solutions to represent a high-dimensional Pareto optimal set and a lack of efficient methods to visualize a large number of solutions representing high-dimensional Pareto optimal solutions showing the trade-offs between the objectives.

We compare the interactive approach to the NSGA-II algorithm [DPAM02], which is one of the most commonly used EMO methods. NSGA-II is an elitist algorithm, where a set of solutions is subjected to selection, crossover and mutation and evolved to find a diverse set of solutions. The selection operation chooses elite solutions with respect to both fitness and diversity, thereby leading to a diverse set of solutions approximating the entire Pareto optimal set.

In this study, the main focus is on demonstrating the potential of applying an interactive multiobjective optimization method in the design of PMSGs involving several relevant objectives against a widely used EMO algorithm. We first formulate a mixed-integer multiobjective optimization problem involving six objective functions for the design and then apply the IND-NIMBUS software [Mie06, OML14] (<http://ind-nimbus.it.jyu.fi/>) to support the DM in finding her/his most preferred Pareto optimal solution. To our best knowledge, this study is the first one considering an interactive multiobjective optimization method in the design of electrical machines.

## 2 Design of permanent magnet synchronous generators

The analytical model for the PMSG [PJH08] used in the optimization is presented in this section. Our implementation of the model has previously been validated in [Man12]. Fig. 1 shows an example cross-section of a PMSG with main geometrical parameters. The flowchart of the design of a PMSG is shown in Fig. 2. After the initial parameters shown in Table 1 are chosen, a suitable stator winding is designed. The number of stator slots and the number of conductors in a slot are defined so that the winding produces a suitable linear current density, which is calculated as  $A = 2mN_{ph}I/(\pi D)$ , where  $m$  is the number of phases,  $N_{ph}$  the number of coil turns in a phase,  $I$  the stator current and  $D$  the stator inner diameter. The dimensions of the stator teeth and the slots are defined so that the stator winding can be fitted into the slots. The yoke size is defined using the relative stator outer diameter  $D_{se}/D_{sy}$ .

A magnetic equivalent circuit is used to obtain the magnetic flux in the air-gap [Hei02]. The reluctances of the magnets, air-gap and iron parts are calculated from  $R_m = l/(\mu_0\mu_r A)$ , where  $l$  and  $A$  are the length and the cross-sectional area of the magnetic flux path, respectively,  $\mu_r$  is the relative permeability of the material and  $\mu_0$  is the permeability of free space. The relative permeability of iron is defined iteratively from a BH curve. Using the magnetic equivalent circuit, the magnetic flux in the air-gap is obtained from

$$\Phi_{\delta,PM} = \frac{\Theta_{PM}}{R_{PM} + R_{\delta} + R_{Fe} + R_{PM}/R_{\delta 2}(R_{\delta} + R_{Fe})}, \quad (1)$$

where  $R_{\delta}$ ,  $R_{PM}$ ,  $R_{Fe}$ , and  $R_{\delta 2}$  denote the reluctances of the air-gap, PMs, iron and leakage reluc-

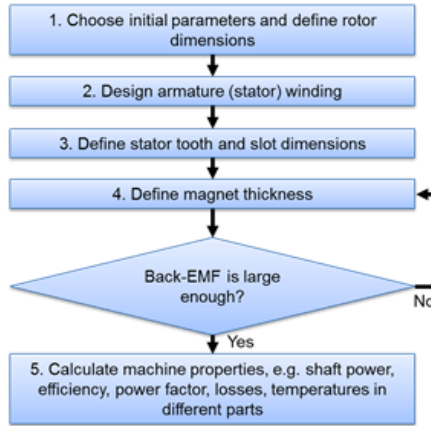


Figure 2: Flowchart of the design process.

tances, respectively. The magnetomotive force  $\Theta_{\text{PM}}$  is in ampere-turns.

When the magnetic flux produced by the magnets is known, the back induced electromotive force (EMF) can be calculated

$$E_{\text{PM}} = \frac{2\pi f k_{w1} N_{\text{ph}} \Phi_{\delta, \text{PM}}}{\sqrt{2}}, \quad (2)$$

where  $f$  is the frequency,  $k_{w1}$  is the winding factor and  $\Phi_{\delta, \text{PM}}$  is the magnetic flux in the air gap produced by the PMs. If the back-EMF is less than 1.05 times the phase voltage, the height of the PMs is increased, and the magnetic equivalent circuit is solved again. This sequence is repeated until the required back-EMF is produced.

After the dimensioning, the resistance and the inductances of the stator winding, shaft power, losses, efficiency and power factor are evaluated. The heat transfer in the machine is also estimated to ensure that especially the PMs are not overheated. A simple thermal resistance network which is described in [Lin99], is used as the thermal model.

### 3 Multiobjective optimization problem formulation

Multiobjective optimization problems are typically of the form

$$\begin{aligned} & \text{minimize/maximize} \quad \{f_1(\mathbf{x}), f_2(\mathbf{x}), \dots, f_k(\mathbf{x})\} \\ & \text{subject to} \quad \mathbf{x} \in S, \end{aligned} \quad (3)$$

with  $k \geq 2$  conflicting objective functions  $f_i : S \rightarrow \mathbb{R}$ . The vector of (design) variables  $\mathbf{x} = (x_1, x_2, \dots, x_n)^T$  belongs to the feasible set  $S \subset \mathbb{R}^n$ . Usually, problem (3) has several optimal solutions called Pareto optimal solutions and we denote the set of Pareto optimal solutions by  $P$ . For simplicity, we present the definition for a case where all the objective functions are to be minimized. A vector  $\mathbf{x}^1$  is Pareto optimal if there does not exist any  $\mathbf{x} \in S$  such that  $f_i(\mathbf{x}) \leq f_i(\mathbf{x}^1)$  for all  $i = 1, \dots, k$  and  $f_j(\mathbf{x}) < f_j(\mathbf{x}^1)$  for at least one index  $j$ . The ranges of the objective function values in the Pareto optimal set are defined by the ideal and the nadir vectors, which represent the best and the worst values that each objective function can achieve in the Pareto optimal set, respectively. A pay-off table [Mie99] is commonly used to find an approximation of the nadir vector. However there exists other approaches for its estimation, see, e.g. [DMC10].

Next, we present the mixed-integer multiobjective optimization problem formulation for the design of a PMSG. There are a total of 14 design variables, 2 of which have discrete values and the other 12 are continuous. The variables, their types and lower and upper bounds are shown in Table 1. The six objective functions are the output power  $P_{\text{out}}$ , torque density  $\rho_{\text{torq}}$ , mass  $m_{\text{tot}}$ , efficiency  $\eta$ , power factor  $\cos(\phi)$  and cost. Output power, torque density, efficiency and power factor should be maximised, whereas mass and cost should be minimized. The objectives are

calculated, respectively, as,

$$\begin{aligned}
P_{\text{out}} &= 3U_{\text{ph}}(I_{\text{q}} \cos(\delta_{\text{a}}) - I_{\text{d}} \sin(\delta_{\text{a}})) \\
\rho_{\text{torq}} &= \frac{T}{m_{\text{tot}}} \\
m_{\text{tot}} &= m_{\text{Fe}} + m_{\text{Cu}} + m_{\text{PM}} \\
\eta &= \frac{P_{\text{out}}}{P_{\text{in}}} \\
\cos(\phi) &= \frac{P_{\text{out}}}{3U_{\text{ph}}I} \\
\text{cost} &= k_{\text{loss}}P_{\text{loss}} + k_{\text{Cu}}m_{\text{Cu}} + k_{\text{Fe}}m_{\text{Fe}} + k_{\text{PM}}m_{\text{PM}},
\end{aligned} \tag{4}$$

where  $T$  is the torque,  $I_{\text{q}}$  and  $I_{\text{d}}$  are the d- and q-components of the stator current, respectively,  $I = \sqrt{I_{\text{d}}^2 + I_{\text{q}}^2}$ ,  $\delta_{\text{a}}$  is the load angle and  $U_{\text{ph}}$  is the phase voltage. Furthermore  $m_{\text{Fe}}$ ,  $m_{\text{Cu}}$ , and  $m_{\text{PM}}$  are the masses of iron, copper and PM material in the machine, respectively,  $P_{\text{out}}$  is the output power,  $P_{\text{in}}$  is the input power,  $k_{\text{Fe}}$ ,  $k_{\text{Cu}}$  and  $k_{\text{PM}}$  are the material prices of iron, copper and magnets, respectively, and  $k_{\text{loss}}$  is the cost coefficient for power losses  $P_{\text{loss}}$ . The costs of the different materials and losses are here estimated to be  $k_{\text{Fe}} = 4 \text{ €/kg}$ ,  $k_{\text{Cu}} = 12 \text{ €/kg}$ ,  $k_{\text{PM}} = 60 \text{ €/kg}$  and  $k_{\text{loss}} = 2 \text{ €/kg}$ .

There are also two constraints that have to be satisfied. First, the stator slot pitch should not be less than 7 mm:  $\tau_{\text{u}} > 7 \text{ mm}$ . The stator slot pitch depends on the total number of stator slots  $Q$  and the stator inner diameter  $D$ :  $\tau_{\text{u}} = (\pi D)/Q$ . The selection of the number of stator slots is associated with the winding design during phase 2 [PJH08, Man12]. The stator inner diameter is defined as  $D = D_{\text{re}} + 2\delta$ , where  $D_{\text{re}}$  denotes the rotor outer diameter that is obtained based on the chosen tangential stress [PJH08]. Furthermore,  $\delta$  denotes the air gap length. Also, the temperature of the PM should not be higher than 100 °C, that is,  $T_{\text{PM}} < 100 \text{ °C}$ , in which  $T_{\text{PM}}$  denotes the temperature of the PMs. This temperature was estimated using a thermal network.

Table 1: Design variables

Symbol	Description	Type	Lower	Upper
$p$	Pole pair number	integer	20	80
$A$	Linear current density (A/m)	real	35000	65000
$J$	Current density (A/m <sup>2</sup> )	real	2000000	6000000
$\delta$	Air gap length (m)	real	0.001	0.05
$D_{\text{re}}/l_{\text{stk}}$	Rotor outer diameter/stack length	real	0.8	5
$w_{\text{PM}}/\tau_{\text{p}}$	Magnet width, relative	real	0.6	0.95
$\sigma_{\text{Ftan}}$	Tangential stress (Pa)	real	21000	48000
$B_{\text{yr}}$	Rotor yoke flux density (T)	real	1.3	1.6
$q$	Number of slots per pole per phase	integer	1	3
$D_{\text{se}}/D_{\text{sy}}$	Stator outer diameter, relative	real	0.8	0.99
$b_{\text{s1}}/\tau_{\text{u}}$	Slot opening, relative	real	0.25	0.75
$b_{\text{s2}}/b_{\text{s1}}$	Slot width, relative	real	0.75	0.95
$h_1/h_3$	Slot height 1, relative	real	0.01	0.1
$h_2/h_3$	Slot height 2, relative	real	0.01	0.1

## 4 Synchronous NIMBUS method

The synchronous NIMBUS method [MM06] has been implemented as the IND-NIMBUS software used in this study. In this section, we briefly outline the method and a pseudo code involves the following steps:

1. **Initialization:** Calculate and show to the DM the ranges of the objective functions in the Pareto optimal set i.e., ideal and nadir vectors.
2. **Starting solution:** Calculate a starting Pareto optimal solution (e.g. a neutral compromise solution [MM06]) and show it to the DM.
3. **Preference information:** Let the DM investigate the Pareto optimal solution and express her/his preference information.

4. **Generation of new solutions:** Once the DM has provided preference information, use it to generate 1-4 new Pareto optimal solution(s) and show them to the DM (the DM can determine how many solutions (s)he wants to see).
5. **Iterative decision:** Let the DM choose a preferred Pareto optimal solution among the solutions presented to her/him and if (s)he wishes to stop, terminate the solution process. Otherwise, go to step 3.

In step 3, the DM provides her/his preference information as a classification of objectives upon investigating a Pareto optimal solution. With the classification, the DM indicates how the current objective function values should be changed to get a more preferred Pareto optimal solution and classifies the objective functions into up to five classes, i.e.

- **Improve:** functions whose values should be improved as much as possible,
- **Improve to value:** functions whose values should be improved to a given value,
- **Satisfactory:** functions whose values are satisfactory at the moment,
- **Impair:** functions whose values are allowed to impair till a given bound, and
- **Change:** functions whose values are allowed to change freely.

Because of the definition of Pareto optimality, the classification is feasible only if some of the objectives are to be improved and some are allowed to impair. By utilizing the classification information, up to four different single objective optimization subproblems are formulated and solved to generate Pareto optimal solutions reflecting the preferences. (It must be noted that if single objective optimization problems are solved using evolutionary algorithms such as GA, the optimality of the solutions generated cannot be guaranteed.) The method also contains an option of generating intermediate solutions between any two Pareto optimal solutions. For further information about the NIMBUS methods, see [MM06].

## 5 Interactive solution process

In this section, we demonstrate the advantages of an interactive method in solving the problem formulated in Section 3. First, we describe the numerical setting and then the interactive solution process using the synchronous NIMBUS method. The DM involved in the decision making process was an expert in the design of PM generators and she was interested in investigating the trade-offs to ultimately design a PMSG. The DM initially mentioned that she was mainly interested in a generator with a minimum mass and cost and maximum efficiency.

As mentioned, in the synchronous NIMBUS method, in each iteration, up to four single objective optimization subproblems are formulated and solved using an appropriate single objective optimization method. In our study, we used a real coded genetic algorithm (GA). Our choice is based on the literature [Hau07, Mie07], where the efficacy of real coded GA in handling nonlinear objective functions with mixed-integer variables has been demonstrated. The parameter setting used was the following: population size = 101, elitism = 1, tournament size = 3, crossover rate = 0.8, mutation rate = 0.1 and degree of mutation = 4. The GA was set to terminate when the difference between the best individuals in the populations in the past 25 generations was smaller than 0.01. Constraints were handled using the adaptive penalty approach [MMT03, MS03].

A summary of the interactive decision making process, i.e., the preference information and the solutions shown to and selected by the DM is given in Table 2, where the latter are denoted in bold face. In this table, the solutions shown to the DM are referred to as  $\mathbf{z}^{i,j}$ , where  $i$  refers to the iteration number and  $j$  the solution number. The preference information provided by the DM is given in the second column.

The interactive solution process was started by showing the ideal and nadir vectors, (0, 16.9, 132000, 0.98, 1, 894000) and (224e+08, 6.01, 289000, 0.7, 0.87, 3910000), respectively, to the DM (to give an idea of the ranges of the objectives) along with the starting solution  $\mathbf{z}^{1,1}$  given in Table 2.

The DM thought that the starting solution had a reasonable output power and torque density and the mass and cost were not very good, but not really bad, either. The efficiency was quite good (0.92). However, the power factor was very poor, only 0.79. The DM wished to improve the

efficiency and the power factor to 0.94 and 0.9, respectively. The efficiency is important, because it affects the energy yield of the generator, and the power factor is also important, because a low power factor means a large reactive power, which in turn increases the size of the frequency converter. At this point, the DM was not interested in the output power, because it was already close to the desired value. Regarding the torque density, the DM decided not to consider it in the first iteration, but to return to it later on. Therefore, the output power and torque density were classified as satisfactory. Because all the solutions considered are Pareto optimal, in every iteration round, something has to be allowed to impair in order to enable an improvement of other objectives. So, for the first iteration, the DM decided to allow the cost and mass to impair.

After the first iteration, three solutions were produced as shown in Table 2. None of them was capable to meet the requirements set by the DM. The power factor was still too low, only 0.87. The efficiency was a little bit higher, but not very high (0.93). This was probably due to the fact that the DM had asked to improve the efficiency to 0.94 and the power factor to 0.9, which are not that high values. Therefore, the DM wanted to see, whether it was possible to further improve especially the power factor and also the efficiency. The DM asked to improve the power factor and the efficiency as much as possible, and allowed everything else to impair without limits.

As a result, four solutions were generated with a very high power factor and efficiency. In all four solutions, the efficiency was around 0.97 and the power factor between 0.97 and 1. However, the mass of the generator was now very large. This result is understandable, because when the mass is increased, the losses are decreased, and, therefore, the efficiency is high. However, a large mass is undesirable in wind power generators. The cost had also impaired a lot, as no limits were set to both mass or cost by the DM. When the mass increases, also the usage of material increases, and this affects the cost as well. The solution  $\mathbf{z}^{2,1}$  had the smallest cost, but  $\mathbf{z}^{2,2}$ , on the other hand, had the smallest mass (165000 kg), when all other solutions had a mass of over 200000 kg. The solution  $\mathbf{z}^{2,2}$  had also a lower efficiency and power factor than the other three solutions, but because all solutions had nevertheless a high efficiency and power factor, the DM decided to continue from  $\mathbf{z}^{2,2}$  because of its lower mass. For the next iteration, the DM wished to improve the mass as much as possible, and allowed the efficiency and the power factor to impair to 0.92 for both objectives. The cost was also allowed to impair a little. The torque density was asked to improve, because decreasing the mass should increase the torque density, if the torque is not decreased at the same time.

Four solutions were generated of which  $\mathbf{z}^{3,3}$  had a very high output power (5.33 MW). However, the DM was aiming at around 3 MW, and thus considered 5.33 MW unnecessarily high. The solution  $\mathbf{z}^{3,3}$  also had too low an efficiency and power factor, so this solution was discarded by the DM. Solutions  $\mathbf{z}^{3,1}$ ,  $\mathbf{z}^{3,2}$  and  $\mathbf{z}^{3,4}$  had a very small mass, between 135000 and 136000 kg, which is the minimum mass that can be obtained. The mass was greatly improved from the previous iteration, and the DM was very happy with this. The solution  $\mathbf{z}^{3,1}$  had a higher cost than solutions  $\mathbf{z}^{3,2}$  and  $\mathbf{z}^{3,4}$ , and  $\mathbf{z}^{3,4}$  had a lower cost and mass and better efficiency than solution  $\mathbf{z}^{3,2}$ , so the DM preferred  $\mathbf{z}^{3,4}$ . Next, the DM wished to aim for a lower cost and to get the output power closer to 3 MW. Therefore, the DM asked to impair the output power to 3 MW and allowed the torque density to impair, as a lower torque was needed to produce the same power. So the DM chose to impair the output power to 3 MW and the torque density to 12.8 Nm/kg. The mass was kept at 136000 kg, the efficiency at 0.92, the power factor at 0.93 and the cost was asked to improve to 1320000 €.

Now three solutions were produced, which can be seen in Table 2. Of them,  $\mathbf{z}^{4,1}$  had a small mass, a good accuracy in the output power and a good torque density. The efficiency and the power factor were above the target and the cost was not as low as expected, but still acceptable. The solution  $\mathbf{z}^{4,2}$  had a little bit more difference in the output power. The efficiency and the power factor were again better than what the DM had asked for, but the cost was higher than in  $\mathbf{z}^{4,1}$ . The solution  $\mathbf{z}^{4,3}$  again had a little bit larger output power than  $\mathbf{z}^{4,1}$  and the torque density close to the target. The efficiency was high (0.96) and the power factor 0.94, which was above the limit. The cost was below the target value (1290000 €). From these three solutions, the DM was happiest with  $\mathbf{z}^{4,3}$ , because of the low cost, and nevertheless a small mass and a good efficiency and power factor. Even though  $\mathbf{z}^{4,3}$  was already very good, the DM still wanted to see whether it would be possible to improve the power factor as it affects the price of the power electronics converter needed. So, the DM asked to improve the power factor and allowed to impair the mass a little, while the cost should not change.

Three solutions were produced. The efficiency and the power factor were improved but the cost



and the mass were impaired. The increase in the mass was rather large, which also affected the cost by increasing it. The increase in the mass was larger than the improvement in the power factor, relatively. Therefore, the DM decided that none of the generated solutions was good enough and concluded that  $\mathbf{z}^{4,3}$  was the best that could be obtained according to the DM's preferences.

To summarize, we studied the design of a PMSG and formulated our problem setup in a manner that the resulting designs would be fit for the use in a megawatt range wind turbine. The energy efficiency of such a machine cannot be heavily compromised in order to maximize the produced electrical power. Besides being energy efficient, the machine must be compact to be installed in the turbine. Also, the use of the PM material needs to be balanced to avoid too high material costs. When interacting with the optimization method, the DM therefore was mainly interested in the efficiency, power factor, mass and cost of the generator, although also output power and torque density were taken into account. It became evident that these contradicting objectives must be assessed simultaneously and that the interactive multiobjective optimization method is a very useful tool for this purpose. It was clearly seen that if the best possible efficiency and/or power factor is aimed at, it will increase the machine size. A larger torque density could be obtained by adding more PM material, which would increase the cost. With the iterative solution process, the DM could learn about the trade-offs between the objectives, learn about what kinds of preferences are feasible and, eventually, find the most preferred solution. Thanks to the insight gained, she could get convinced of the goodness and justify the choice of the final solution well.

From the starting point, the generator design was greatly improved, the mass was decreased from 140000 kg to 135000 kg, the efficiency was improved from 0.9 to 0.96, and the power factor was improved from 0.79 to 0.94. The output power changed from 3.66 MW to 3.13 MW, and the torque density decreased from 15.6 Nm/kg to 13.6 Nm/kg. The cost decreased from 1700000 € to 1300000 €. So, by decreasing the torque density and the output power, a very good improvement was made in the efficiency, the power factor and also in the mass. The cost was also improved. The cost is highly affected by the usage of materials, and especially the PM material is expensive. Therefore, because the DM required a good efficiency and power factor, the cost had to be sacrificed in order to get a good performance. However, during the last iteration, it became evident that obtaining a very good power factor will also increase the mass of the PMSG. The DM at this point decided that the mass increased too much, as can be seen from the last three results, and decided that it was better to compromise in the power factor.

Besides the interactive method, an implementation of the NSGA-II algorithm in MATLAB called NPGM [Lin] was used to solve the same problem. A population of 200 individuals and a stopping criterion of 150 generations were used in addition to standard parameter settings described in the software. The final set of solution obtained was provided to the DM. Among the 200 solutions obtained, only 15 had a power factor and an efficiency greater than 0.9, which were of interest to the DM. All the 15 solutions have a larger mass and a larger cost than those found using the interactive method. In addition, the output power in all of the solutions was close to the 3 MW value and the torque density was smaller than what was obtained by the interactive method. It was not easy for the DM to compare many solutions with six components. However, specifically, two solutions (3030000, 8.0922, 216000, 0.9770, 0.9515, 1980000) and (3180000, 9.7854, 191000, 0.9574, 0.9919, 2110000) were considered to be preferred among the 15 solutions. However,  $\mathbf{z}^{4,3} = (3126584.68, 13.62735299, 134523.237, 0.95916683, 0.943504748, 1285583.22)$  obtained using the interactive method was still the most preferred solution as the preferred NPGM solutions had an approximately 30% to 35% higher mass and a 35% to 39% higher cost, respectively.

When compared to widely used, noninteractive methods, the DM found several advantages in using the interactive method. First, because of having as many as six objectives, the Pareto optimal set is extremely difficult to be represented well and to visualize in an informative way. So, for the DM, handling the 6-dimensional vectors so that she could clearly see the contradictions between the objectives was very challenging. The interactive method offered the DM a comfortable way to handle a small amount of Pareto optimal solutions at a time, and offered a tool to help her to conveniently gain insight about the interdependencies among the objectives and find her preferred solution. Secondly, as in this case (which is rather typical), the DM was more interested in certain areas of the Pareto optimal set, and it is beneficial to get more solutions in those areas and avoid others that are not seen so crucial for the DM. Thus, in that case, not so many solutions are needed in those areas of the Pareto optimal set. By using the interactive method, the DM could, during the optimization process, target the optimization to those areas that she found more important, which is something that cannot be so easily done with noninteractive methods. This

also saves computational resources.

## 6 Conclusions

In this work, we identified six different objective functions pertaining to the design of a permanent magnet synchronous generator and formulated a corresponding mixed-integer multiobjective optimization problem. With this, we demonstrated the benefits of formulation all relevant objectives in the problem. Methods such as weighted sum, evolutionary algorithms etc. are commonly used in the literature. However, they are not that well suited to consider preference information of a DM or a large number of objectives. Furthermore, they do not support learning about the problem and the trade-offs involved. Hence, in this article we demonstrated the advantages of applying an interactive method, i.e., the synchronous NIMBUS method in solving the multiobjective optimization problem of electrical machines.

As a result, an optimal design for a permanent magnet synchronous generator was produced based on the DM's preferences. During each iteration of the interactive solution process, the DM was given three or four different Pareto optimal solutions. She then chose one according to her preferences, and also decided how the solution should be modified to become more preferred in the next iteration. Because all solutions produced by NIMBUS are Pareto optimal, the DM also had to allow impairment of some objectives while hoping to improve others. In this case, the DM decided to sacrifice the torque density in order to get a better performance of the machine with a reasonable cost and a small mass.

During the optimization process, the DM noticed that compared to widely used noninteractive multiobjective optimization methods, the interactive method offers a way to handle several objectives in a very useful and informative way. It also allowed the DM to learn about how the choices between the different objectives affect the generated solutions, and offered a possibility to learn about the interdependencies among the objectives and the trade-offs that have to be made as well as to adjust the preferences. With as many as six objectives, handling the Pareto optimal set without any tools would be extremely difficult for the DM. The interactive optimization method is a good approach, as it offers a way to better understand what kind of solutions are possible to achieve and what are not. Another advantage is that it allows the DM to target the search of the most preferred solution to certain areas of the Pareto optimal set of solutions, meaning that more resources can be devoted to certain areas of the design space. This in turn may help to reduce the amount of computation time used for the optimization, which may enable using more accurate but computationally heavy models for the electrical machines, such as finite element methods.

To conclude, the entire solution process using the interactive method proved out to be extremely interesting and informative to the DM, and an optimal solution which satisfied the DM was found and thanks to learning, she could get convinced of the goodness of the final solution. In the future, interactive multiobjective optimization methods could be used with different electrical machine topologies, or different types of models. This study forms a basis for further, more extensive use of interactive methods in the field of electrical machine design.

## References

- [BCW15] T. Bazzo, R. Carlson, and F. Wurtz. Wind power PMSG optimally designed for maximum energy proceeds and minimum cost. In *2015 IEEE 24th International Symposium on Industrial Electronics (ISIE)*, pages 1464–1470, June 2015.
- [BDMS08] J. Branke, K. Deb, K. Miettinen, and R. Slowinski (eds.). *Multiobjective Optimization: Interactive and Evolutionary Approaches*. Springer-Verlag, Berlin, Heidelberg, 2008.
- [BVB08] S. Brisset, D. Vizireanu, and P. Brochet. Design and optimization of a nine-phase axial-flux PM synchronous generator with concentrated winding for direct-drive wind turbine. *IEEE Transactions on Industry Applications*, 44(3):707–715, May 2008.
- [DI13] Y. Duan and D. M. Ionel. A review of recent developments in electrical machine design optimization methods with a permanent-magnet synchronous motor benchmark study. *IEEE Transactions on Industry Applications*, 49(3):1268–1275, May 2013.

- [DJT16] A. Daghigh, H. Javadi, and H. Torkaman. Design optimization of direct-coupled ironless axial flux permanent magnet synchronous wind generator with low cost and high annual energy yield. *IEEE Transactions on Magnetics*, 52(9):1–11, Sept 2016.
- [DMC10] K. Deb, K. Miettinen, and S. Chaudhuri. Towards an estimation of nadir objective vector using a hybrid of evolutionary and local search approaches. *IEEE Transactions on Evolutionary Computation*, 14(6):821–841, Aug 2010.
- [DPAM02] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan. A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, 6(2):182–197, Apr 2002.
- [Dub04] M. R. J. Dubois. *Optimized Permanent Magnet Generator Topologies for Direct-Drive Wind Turbines*. Delft University of Technology, 2004.
- [ERN15] E. L. Engevik, A. Røkke, and R. Nilssen. Evaluating hybrid optimization algorithms for design of a permanent magnet generator. In *2015 Intl Aegean Conference on Electrical Machines Power Electronics (ACEMP), 2015 Intl Conference on Optimization of Electrical Electronic Equipment (OPTIM) 2015 Intl Symposium on Advanced Electromechanical Motion Systems (ELECTROMOTION)*, pages 711–718, Sept 2015.
- [Gra96] Anders Grauers. *Design of Direct-driven Permanent-magnet Generators for Wind Turbines*. Technical report - School of Electrical and Computer Engineering, Chalmers University of Technology, Göteborg, Sweden, no: 292. 1996.
- [Hau07] R. L. Haupt. Antenna design with a mixed integer genetic algorithm. *IEEE Transactions on Antennas and Propagation*, 55(3):577–582, Mar 2007.
- [Hei02] T. Heikkilä. *Permanent Magnet Synchronous Motor for Industrial Inverter Applications - Analysis and Design*. PhD thesis, Lappeenranta University of Technology, 2002.
- [HMN06] E. Heikkola, K. Miettinen, and P. Nieminen. Multiobjective optimization of an ultrasonic transducer using NIMBUS. *Ultrasonics*, 44(4):368–380, Nov 2006.
- [HMS11] J. Hakanen, K. Miettinen, and K. Sahlstedt. Wastewater treatment: New insight provided by interactive multiobjective optimization. *Decision Support Systems*, 51(2):328–337, May 2011.
- [LC08] H. Li and Z. Chen. Overview of different wind generator systems and their comparisons. *IET Renewable Power Generation*, 2(2):123–138, June 2008.
- [Lin] S. Lin. *NGPM - A NSGA-II Program in MATLAB*, url = <https://se.mathworks.com/matlabcentral/fileexchange/31166-ngpm-a-nsga-ii-program-in-matlab-v1-4>, version = 1.4.
- [Lin99] Joachim Lindström. Development of an experimental permanent-magnet motor drive. Licentiate thesis, Chalmers University of Technology, Gothenburg, Sweden, April 1999.
- [Man12] A. Manninen. Evaluation of the effects of design choices on surface mounted permanent magnet machines using an analytical dimensioning tool. Master’s thesis, Aalto University School of Electrical Engineering, Espoo, Finland, 2012.
- [Mie99] K. Miettinen. *Nonlinear Multiobjective Optimization*. Kluwer Academic Publishers, Boston, 1999.
- [Mie06] K. Miettinen. IND-NIMBUS for demanding interactive multiobjective optimization. In T. Trzaskalik, editor, *Multiple Criteria Decision Making '05*, pages 137–150, Katowice, 2006. The Karol Adamiecki University of Economics in Katowice.
- [Mie07] K. Miettinen. Using interactive multiobjective optimization in continuous casting of steel. *Materials and Manufacturing Processes*, 22(5):585–593, May 2007.
- [MM06] K. Miettinen and M. M. Mäkelä. Synchronous approach in interactive multiobjective optimization. *European Journal of Operational Research*, 170(3):909–922, May 2006.

- [MMT03] K. Miettinen, M. M. Mäkelä, and J. Toivanen. Numerical comparison of some penalty-based constraint handling techniques in genetic algorithms. *Journal of Global Optimization*, 27:427–446, Dec 2003.
- [MS03] Z. Michalewicz and M. Schoenauer. Evolutionary algorithms for constrained parameter optimization problems. *Evolutionary Computation*, 4(1):1–32, Mar 2003.
- [OML14] V. Ojalehto, K. Miettinen, and T. Laukkanen. Implementation aspects of interactive multiobjective optimization for modeling environments: the case of GAMS-NIMBUS. *Computational Optimization and Applications*, 58(3):757–779, July 2014.
- [PJH08] Juha Pyrhönen, Tapani Jokinen, and Valéria Hrabovcová. *Design of Rotating Electrical Machines*. John Wiley & Sons, Chichester, 2008.
- [PK15] J. H. J. Potgieter and M. J. Kamper. Design optimization of directly grid-connected PM machines for wind energy applications. *IEEE Transactions on Industry Applications*, 51(4):2949–2958, July 2015.
- [TA14] N. Taran and M. Ardebili. A novel approach for efficiency and power density optimization of an axial flux permanent magnet generator through genetic algorithm and finite element analysis. In *2014 IEEE 23rd International Symposium on Industrial Electronics (ISIE)*, pages 709–714, June 2014.
- [TABD12] H. Tiegna, Y. Amara, G. Barakat, and B. Dakyo. Overview of high power wind turbine generators. In *2012 International Conference on Renewable Energy Research and Applications (ICRERA)*, pages 1–6, Nov 2012.
- [VSD10] H. Vansompel, P. Sergeant, and L. Dupre. Optimized design considering the mass influence of an axial flux permanent-magnet synchronous generator with concentrated pole windings. *IEEE Transactions on Magnetics*, 46(12):4101–4107, Dec 2010.
- [VZI06] S. Vaez-Zadeh and A.H. Isfahani. Multiobjective design optimization of air-core linear permanent-magnet synchronous motors for improved thrust and low magnet consumption. *IEEE Transactions on Magnetics*, 42(3):446–452, March 2006.

Table 2: Summary of the interactive solution process

Interaction number	Preference information	Solutions generated
0	Starting solution	$\mathbf{z}^0 = (36.6e+6, 15.6, 14e+4, 0.92, 0.79, 17e+5)$
1	Output power = Satisfactory Torque density = Satisfactory Mass = Improved to 16.2e+4 Efficiency = Improved to 0.94 Power factor = Improve to 0.9 Cost = Impair to 202e+04	$\mathbf{z}^{1,1} = (3429425.97, 13.91232166, 148795.1693, 0.931679815, 0.864650418, 1764877.06)$ $\mathbf{z}^{1,2} = (3309341.075, 14.22671395, 139781.8711, 0.935879161, 0.872129102, 1471630.88)$ $\mathbf{z}^{1,3} = (3523987.168, 14.42646069, 147351.0242, 0.932298658, 0.869186441, 1760233.601)$
2	Output power = Satisfactory Torque density = Satisfactory Mass = Impair Efficiency = Improved Power factor = Improved Cost = Impair	$\mathbf{z}^{2,1} = (3042521.203, 8.446304104, 208241.6454, 0.972821161, 0.98078737, 1758764.832)$ $\mathbf{z}^{2,2} = (3220170.189, 11.46112469, 165290.1903, 0.955956663, 0.957071241, 1812793.121)$ $\mathbf{z}^{2,3} = (3004340.158, 7.445393663, 232480.0931, 0.976133826, 0.998309358, 1920887.537)$ $\mathbf{z}^{2,4} = (3124451.069, 13.3152913, 136564.704, 0.966314028, 0.965433737, 1373313.059)$
3	Output power = 3140000 Torque density = Improved Mass = Improved Efficiency = Impair to 0.92 Power factor = Impair to 0.92 Cost = Improve	$\mathbf{z}^{3,1} = (3591825.202, 16.06994309, 135735.6435, 0.926063239, 0.944464528, 1761201.852)$ $\mathbf{z}^{3,2} = (3240926.313, 14.55409568, 135566.4104, 0.923773566, 0.969884868, 1519851.784)$ $\mathbf{z}^{3,3} = (5336363.299, 25.29118953, 138445.1352, 0.857101251, 0.793967077, 2977915.822)$ $\mathbf{z}^{3,4} = (3246094.027, 14.608883359, 135050.1394, 0.925303517, 0.974186781, 1478803.511)$
4	Output power = 3000000 Torque density = 12.8 Mass = 136000 Efficiency = 0.92 Power factor = 0.93 Cost = Improved to 1320000	$\mathbf{z}^{4,1} = (3035718.353, 12.99741026, 139110.6084, 0.944230653, 0.998754879, 1397813.796)$ $\mathbf{z}^{4,2} = (3128197.888, 13.75806472, 136272.4318, 0.938345035, 0.985984045, 1412967.444)$ $\mathbf{z}^{4,3} = (3126584.68, 13.62735299, 134523.237, 0.95916683, 0.943504748, 1285583.22)$
5	Output power = Satisfactory Torque density = Impair Mass = Impair Efficiency = Satisfactory Power factor = Improve Cost = Satisfactory	$\mathbf{z}^{5,1} = (3023372.098, 12.19258596, 146383.2201, 0.952660535, 0.999316911, 1397791.852)$ $\mathbf{z}^{5,2} = (2961295.08, 11.72349397, 152255.9309, 0.933005272, 0.998075218, 1520598.411)$ $\mathbf{z}^{5,3} = (3088954.105, 12.35057073, 145889.6913, 0.964125388, 0.977875203, 1377388.139)$