Abstract— In industrial applications there is a constant demand for increasing the general performance of machines. This proposes the problem of designing the machine with the best qualities within given constraints. Hence analytical models of machines tend to be complicated when increasing the details of the model, numerical tools seem to be promising choices for calculations. The industry also seeks for methods to reduce costs and also time of prototyping, a substantial part of design processes. This legitimates the research of simulation methods, their improvement to get closer and closer to reality. The goal of this paper is to present and exemplify the simulation and numerical optimization of a switched reluctance motor.

I. OVERVIEW OF THE PROBLEM

A. About Optimisation Methods

An optimization problem is represented as the following: given a function \( f(x) \) where \( x \) is a vector of values, we seek a vector \( x_0 \) such that for every \( x \) (within given constraints), \( f(x_0) \geq f(x) \) (in case of a maximization problem; or \( f(x_0) \leq f(x) \) in case of a minimization problem). The optimal value would be easy to obtain if one knew all possible values of \( f \) (e.g. in a discrete problem), but even by low-level complexity this method is not effective due to the amount of computation it requires. \( f \) is a target function of desire, meaning a quantity to be optimized e.g. in machine design the efficiency, average torque or starting torque. \( f \) can also be a combination of multiple quantities, representing that various quantities are to be optimized at the same time (in a compromised way) with weights according to their importance in the end requirement. This is called multi-objective optimization, where production cost are typically incorporated next to a performance attribute as main target. [1] and [2] presents multi-objective optimizations of electric machines.

The motivation to find the maximum in an optimization problem is understandable, however, in engineering applications one might be satisfied with a non-maximal solution if it is feasible considering predefined conditions. E.g. one might not need to hunt the global maximum of the efficiency of a machine, but only to work it above a certain value. This leads to constraint satisfaction problems.

For observing the effect of the variables on the function, analytical solutions of the electromagnetic field in closed form would serve us the best, but this approach leads to extraordinarily difficult calculations when applying Maxwell's equations analytically to complex layouts such as electric machines. However, [2] presents a semi-analytical method aiming to keep the mentioned benefits.

Literature provides several approximative formulas for characteristics of electric machines (where equations cannot be derived by physics evidently), with which a target function can be constructed and optimization can be performed, such as in [3]. A possible disadvantage of the usage of such formulas is their experiential nature, bearing the risk of error when applied to a new problem.

If instead of experiential formulas, one wants to work with Maxwell’s equations directly, numerical solutions for differential equations are a possible way, though with growing details they require a vast amount of time to compute. Present work incorporates finite element method (hence FEM) to calculate the electromagnetic field in the machine.

From a starting point \( x \) to find the optimal \( x_0 \) (commonly called local search) various algorithms exist. One can perform random walk with steps in arbitrary directions and evaluating the change of the target function for conclusions. Hill climbing algorithms seek and take steps towards the biggest gradient of \( f \) in each point, ensuring the achievement of an optimum which on the other hand might not be a global one but just local. Variations aim to increase the efficiency of this method, e.g. stochastic hill climbing randomly chooses between uphill directions with a probability varying with steepness. Simulated annealing, inspired by metallurgy, probabilistically decides if moving to a neighboring state of not. Genetic algorithms, within the class of evolutionary algorithms mimic the process of natural selection to find feasible values.

B. The Motor as Subject of Optimisation

A 3-phase switched reluctance motor (hence SRM) is given with the geometry shown in Fig. 1. The basic motor specifications are shown in Table I.

| TABLE I |
|-----------------|-----------------|
| Num. of stator poles | 6               |
| Num. of rotor poles | 8               |
| Rated power         | 11 kW           |
| Rated speed         | 1500 1/min      |
| Rated torque        | 70 Nm           |
| Peak Torque         | 168 Nm          |
| Rated current mean  | 46.5 A          |
| Motor efficiency    | 90%             |

Being a salient pole machine, the inductance inside the air gap varies along the circumference. This results in reluctance torque, by which the SRM is moved in operation. This reluctance torque is the physical quantity affecting the operative characteristics of the machine. Its value depends on the air gap inductance. This leads to the geometric parameters
being the root affectors of operation, thus being the yet unknown values to be found in order to achieve optimal capabilities.

![Fig. 1. The geometry of the given switched reluctance motor.](image)

The complexity and hence computation time of the optimization increases as we take more and more variables as unknowns. Because of the demonstrative nature of present work I restrain the procedure to 2 dimensions and only 5 variables (shown in Fig. 2):
- the face width of the rotor poles,
- the stem width of the rotor poles,
- the diameter of the rotor poles,
- the diameter of the rotor at the stem of the rotor poles
- and the face width of the stator poles.

![Fig. 2. The design variables of the given switched reluctance motor shown with highlighted lines.](image)

The scope of present optimization does not cover the drive and control, the voltage or current values and waveforms applied to the machine. The coils are driven by simple current pulses, each phase conducting a constrained constant current for one-third of the period. One phase consists of two coils, which surround the poles of one pole pair.

II. THE PROGRAM PERFORMING THE OPTIMIZATION

A. The Structure of the Program

Present optimization aims to find the optimal value of the above listed geometric parameters to produce maximal starting torque. The program written for present machine's optimization consists of four modules (see Fig. 3). The main one is the optimization module, which can be viewed as the nest of the others. It is written in Python programming language. The program starts out with an initial vector $x$ of geometric parameters to be optimized, and already knowing which points are to be connected with what kind of curve, generates the geometry file in the common $dxf$ format. The program then calls the FEM module to assemble the model of the machine (with the components being made of different materials, the coils and the rotating component), then to solve the model for the electromagnetic field and to calculate other quantities of interest. The results are then fed back to the optimization module, which, after evaluation, determines the next step.

![Fig. 3. The structure of the program with the four modules.](image)

B. The FEM Modules

The commercial software MagNet by Infolytica Corporation was used to take care of the finite element modeling and solving, which can be programmed in Visual Basic programming language to perform a desired flow. This basic flow consists of:

1. importing the machine geometry data,
2. defining the material properties of components,
3. defining the sources of the electromagnetic field,
4. defining the attributes of the moving component,
5. setting the simulation parameters (starting and ending times, time step),
6. solving the concerning differential equation for the field data,
7. analyzing the field data and calculating torque values,
8. and finally exporting the results.

In present work the target quantity is the starting torque. The differential equation to solve is Ampère's law, which is commonly used in similar problems: $\nabla \times \nabla \times A = J$, for $\mu$ being the magnetic permeability, $A$ the magnetic vector potential and $J$ the electric current density. As adding a gradient field does not change this equation, it is required to choose a unique vector potential. This is done by defining $\nabla A = 0$ (Coulomb gauging). Aside the concerning magnetic boundary conditions between the different materials inside the motor, on the model outer boundary the flux density normal component $B_n = 0$ and the vector potential $A_z = \text{const.}$ are defined. The B-field is then acquired as being the rotation
of $A$: $B = \text{rot } A$. The field is illustrated in Fig. 4., where the maximum flux density resulted 0.49 T.

Fig. 4. The magnetic field inside the motor with the lines representing the magnetic flux.

C. The Optimization Method

The optimization repetitively performs a unit step in 1 dimension and if the new point satisfies the defined constraints, the change of the target quantity will be evaluated. If after a step there is increase in the target quantity, the optimizer saves that step, otherwise it steps back. The algorithm looks as follows:

1. start with a given $x_{m0} = (x_1, x_2, \ldots, x_n)$ as $x_m$
2. calculate $f(x_m)$
3. for K iterations
4. assign $x_{m+1} = x_m$
5. randomly choose an index $i$ between 1 and $n$
6. in $x_{m+1}$ modify $x_i$ by $\Delta x_i$
7. if for any $i$ in $x_{m+1}$, $x_i > x_{i,\text{max}}$ or $x_i < x_{i,\min}$, jump to the next iteration
8. calculate $f(x_{m+1})$
9. if ($f(x_{m+1}) > f(x_m)$ assign $x_m = x_{m+1}$

The stopping criterion of the algorithm is performing K iterations, meaning the time available for computation. The $\Delta x_i$ steps of modifying $x_i$ for each dimension are fixed and defined according to the magnitude of the corresponding parameter at the starting $x$. The geometry generation and FEM calculation is performed in step 8, where the optimizer program calls the geometry generator script and the FEM model builder and solver.

III. RESULTS

After K = 50 iterations the optimization achieved 2.5% increase in the starting torque of the machine. The change of machine parameters are shown in Table II. The increase in the starting torque is notable, but the parameters did undergo only small changes. Taking bigger steps in the parameter space can lead to the vicinity of a farther optimum faster, but it might not find the actual optimum, getting to which one would require finer steps. On the other hand, taking small steps mean slower movement in the parameter space, requiring more computation time. To exploit the advantages of both, adaptive algorithm is needed.

IV. CONCLUSION

A simple method to optimize a few geometric parameters of a switched reluctance motor has been performed. It is demonstrated that the method is capable of increasing the performance of a machine by finding points in the parameter space which lead to higher values of the target quantity. The result greatly depends on the optimization algorithm, as the more complex the algorithm is, or the more it is sensitive to the changing of the target quantity the change of the point in the parameter space, the more likely it is to find a better or even optimal value of the target function. It also depends on the number of design parameters, actually the design freedom, but the number representing degrees of freedom it also means that for increasing this, one needs much more computation capacity and time to perform relevant exploration in the parameter space. For industrial usage, more complex target functions are needed, which incorporate mechanical, thermodynamical, financial and also manufacturing aspects to show actual applicability. Especially in the case of switched reluctance motors, the control method greatly influences the performance of the machine. Thus, the control quantities, the field sources must be incorporated in such optimization, which in this paper was omitted due to the scope of the study. Furthermore, the reality and reliability of a simulation result is always questionable when one arrives to the real world application of a design. To verify simulation results, creation of machine prototypes are still needed, so one is able to perform measurements on the real, actual value quantities of interest.

REFERENCES