Robust and Reliability-Based Design Optimization of Electromagnetic Actuators Using Heterogeneous Modeling with COMSOL Multiphysics and Dynamic Network Models

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Abstract: For an exemplary electromagnetic actuator used to drive a Braille printer, a design optimization was performed. The optimization involves stochastic variables and comprises nominal optimization, robustness analysis and robust design optimization. A heterogeneous model simulates the static and the dynamic behavior of the actuator and its non-linear load. It consists of a network model in SimulationX and a static magnetic FEA model in COMSOL Multiphysics. The network model utilizes look-up tables of the magnetic force and the flux linkage computed by the FEA model. The optimization tool OptiY controls the design variables of the models during the optimization and the stochastic analysis. In order to reduce the computational effort we used response surfaces instead of the system model in all stochastic analysis and optimization steps. This allows Monte-Carlo simulations to be applied. The optimization itself uses gradient-based algorithms.

Keywords: Electromagnetic Actuator, Heterogeneous Modeling, Robust Design Optimization, RDO.

1. Introduction

Model based design optimization is on the rise in product development. Normally, the models used therein consider nominal values of the design and ambient parameters. However, deviations of these parameters influence function and reliability. They lead to rejections, functional deviations, and failures. Therefore, the design and ambient parameters have to be considered with their stochastic characteristics if a certain robustness or reliability of the system has to be met. We describe an optimization methodology that includes stochastic variables for an exemplary electromagnetic actuator.

2. Electromagnetic Actuator Model

Electromagnetic actuators are used, when fast actuation, medium forces and medium strokes are required. Although their design varies in a very wide range, they always consist of an armature, a yoke with a back iron, a working air gap and a parasitic guiding air gap and a coil as a minimum of elements (Fig. 1). The armature is connected to a mechanical load characterized by a mass to be moved and an elastic or plastic counterforce. Our example is a Braille printer with a needle which embosses the paper and a return spring.

In the following, this simple design is used to show the modeling approach and the optimization steps we applied. However, more complicated arrangements, containing e. g. permanent magnets, more than one coil, or more sophisticated iron parts, can also be analyzed and optimized in the same manner.

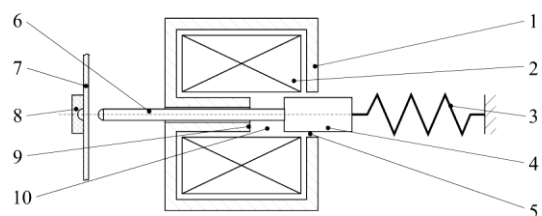

Figure 1. Braille printer with electromagnetic actuator; 1 back iron, 2 coil, 3 return spring, 4 armature, 5 guiding air gap, 6 needle, 7 paper sheet, 8 die, 9 yoke, 10 working air gap

2.1 Governing Equations

Design and optimization of magnetic actuators is a challenging matter due to the bidirectional cause-effect relations between electric and magnetic field, nonlinear magnetic material behavior, and the fact that often a nonlinear load is driven by the actuator. Mostly, requirements concerning both the static and the dynamic behavior have to be considered.

The static behavior is given by Maxwell's equation using the magnetic vector potential $\mathbf{A}$ [1], when the time derivatives disappear:

$$\nabla \times \left(\frac{1}{\mu} \nabla \times \mathbf{A} \right) = \mathbf{j}_{\mathrm{ext}} \cdot \tag{1}$$

$\mathbf{j}_{\mathrm{ext}}$ is the external current density, σ and μ the conductivity and the permeability of the material, respectively. Based on the flux density $\mathbf{B}$ derived from the solution of Eq. 1 as $\mathbf{B} = \nabla \times \mathbf{A}$, the magnetic force $\mathbf{F}$ on the armature can be calculated by different methods, e. g. by integration of the Maxwell's surface stress-tensor on an arbitrary surface S surrounding the armature, as provided by COMSOL Multiphysics:

$$\mathbf{F} = \int_S \left[\frac{1}{\mu_0} (\mathbf{B} \cdot \mathbf{n}) \mathbf{B} - \frac{1}{2\mu_0} \mathbf{B}^2 \cdot \mathbf{n} \right] dS \cdot \tag{2}$$

However, the result of this method is sensitive to mesh discretization and integral contour position. Therefore, in practical applications, the use of the average forces by several contours is adviced [2].

Eq. 1 also allows the flux linkage Ψ to be calculated which is necessary as well as the magnetic force to compute the dynamic behavior of the actuator-load system by a network model (s. section 2.3):

$$\Psi = \int_{\mathbf{A}_\Psi} \mathbf{B} \, d\mathbf{A}_\Psi \tag{3}$$

The following sections describe the models that incorporate these equations.

2.2 Static Magnetic Model

The static behavior is modeled by the FEA method. We assumed the problem to be axially symmetric with currents in the angular direction only. We applied the emqa application mode provided by COMSOL Multiphysics 3.5a and MATLAB scripting to build the model as an m-file. All design parameters needed to build the model geometry and to be changed during the optimization process are loaded from an input m-file. Similarly, the non-linear ferromagnetic material is involved in the form $\mu_{\mathrm{rel}}(B)$ as a look-up table stored in an ASCII file (Fig. 2). The surrounding air is built as a semi-circle around the whole arrangement. Meshed by free meshing with normal mesh size, we obtain about 5,000 to 10,000 DOF depending on the geometry. The UMFPACK direct solver was applied.

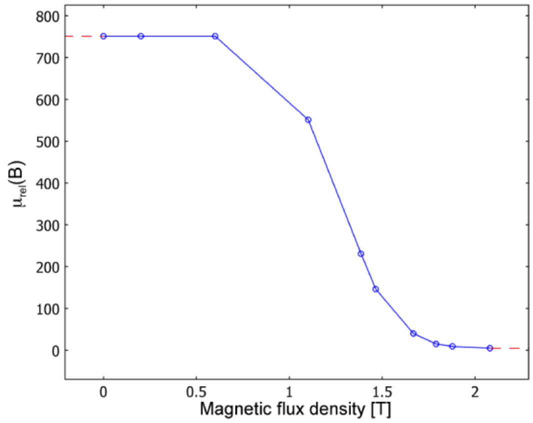

Figure 2. $\mu_{\mathrm{rel}}(B)$ behavior of the nonlinear magnetic material steel St3

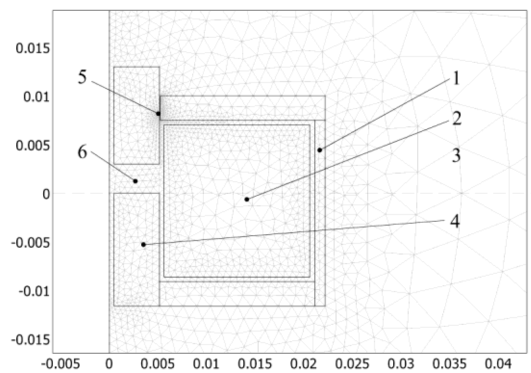

Figure 3. Static FEA model of the electromagnetic actuator (cutout); 1 back iron, 2 coil, 3 air, 4 armature, 5 guiding air gap, 6 working air gap

The model computes the magnetic force $\mathbf{F}(\mathbf{i}, \mathbf{x})$ and the flux linkage $\mathbf{\Psi}(\mathbf{i}, \mathbf{x})$ for a matrix of discrete values of the magnetizing current $\mathbf{i} = i_1, \ldots, i_n$ in the coil and the position $\mathbf{x} = x_1, \ldots, x_m$ of the armature. The results are written to ASCII files. Furthermore, the model calculates and stores the coil resistance and the volumes of the armature and of the actuator as a whole.

One major obstacle is to ensure that the model is working properly in the whole parameter space, particularly regarding the geometry and the mesh. This is a precondition that must be met for the application of such optimization algorithms that require a valid result at every point in the parameter space, e. g. gradient-based algorithms. For this purpose, some logical operations check the geometry before the model is built. If an inconsistence occurs a result is outputted equivalent to a malfunction of the system.

2.3 Heterogeneous Dynamic Model

State of the art in time-efficient dynamic simulation of magnetic actuators is modeling with networks that include look-up tables computed from FEA models [3]. As a general rule, there a two options: the non-conservative formulation of the physical relations in a signalflow diagram or the conservative formulation in a generalized Kirchhoffian network [4, 5, 6]. Both approaches allow coupling with finite element analysis. Because the latter approach is a little clearer, we used it. Figure 4 shows the network model of the electromagnetic actuator of the Braille printer realized in SimulationX [7].

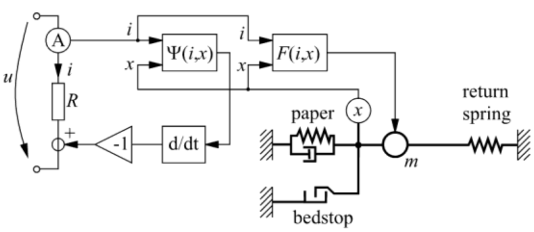

Figure 4. Dynamic Network model of the Braille printer, coil resistance R, armature mass m

The system dynamics can be computed using the computed static behavior $\mathbf{F}(\mathbf{i}, \mathbf{x})$ and $\boldsymbol{\Psi}(\mathbf{i}, \mathbf{x})$. The ODE for the mechanical dynamics describes the dynamic behavior of the actuator with the load $F_{\mathrm{load,x}}$ for the one-dimensional motion along the coordinate x:

$$m\,\ddot{x} = F_{mag,x}(i,x) - F_{load,x}(x). \tag{4}$$

The terminal voltage u consists of the Ohmic voltage drop iR and the induced back-emf (electromotive force) $\mathrm{d}\Psi/\mathrm{d}t$. This is given by Kirchhoff's voltage law:

$$u = i\,R + \dot{\Psi}(i,x). \tag{5}$$

However, this approach neglects some dynamic effects, e. g. eddy currents.

Further, dynamic FEA models have been published that include the ordinary differential equation of the motion without previous computation of static look-up tables, e. g. with moving meshes [8]. This allows the eddy currents to be included in the simulation. However, this approach restricts itself to simple arrangements with respect to the computing time.

3. Optimization of the Actuator

The design optimization comprises four steps. In the first design optimization step we used the static model for finding an optimized design of the electromagnetic actuator. In the second step, we optimized the dynamic behavior of the Braille printer system starting with the optimized design from the first step. The third step comprises a tolerance and robustness analysis that calculates the probability distributions of system behavior variables from the distributions of the design parameters. This enables the system failure probability to be deduced. In the final step, a robust design of the system was calculated that minimizes the system failure propability. For arranging the data flow we used the OptiY tool [9].

3.1 Nominal Optimization Using the Static Magnetic Model

The optimization starts with a preliminary design representing a rough idea of a design that would fulfill the requirements. It may be found by an analytical or empirical approach or by a rough and fast pure network model. A sensitivity analysis shows the importance of the design variables on the performance. This is a crucial step since the importance of the design variables is usually dependent on the position of the design point in the parameter space.

Starting with a slim actuator, a more compact design was found that fulfills requirements with regard to the magnetic force at maximum stroke, power consumption and overall dimensions (Fig. 5, 6). Seven design variables (six dimensions and the coil current) were involved in the optimization using the Hooke-Jeeves algorithm.

The optimization based on the static FEA model of the actuator allows only constraints and objectives with regard to the static behavior to be considered. With the aim of a system optimization we developed a heterogeneous model of the system dynamics.

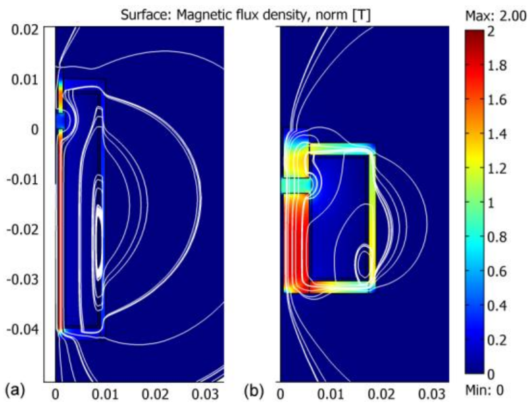

Figure 5. Nominal optimization based on the static model, (a) slim preliminary design, (b) compact optimum design

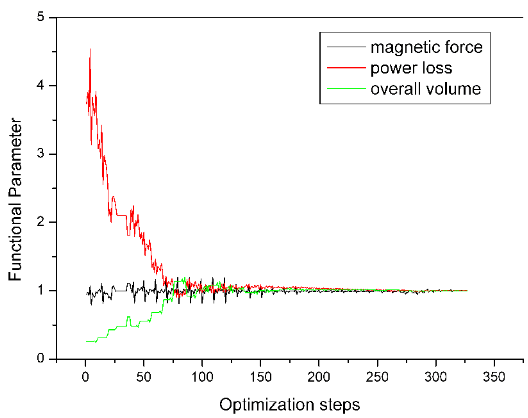

Figure 6. Nominal optimization based on the static model, development of the functional behavior relative to the optimum

3.2 Nominal Optimization Using the Heterogeneous Dynamic Model

The nominal optimization with regard to the system dynamics bases on the model described in Sec. 2.3. It must be remembered that the look-up tables are valid only for the geometry they are computed for when they are applied in design optimization. Therefore, they have to be computed by the FEA model in every optimization step. This is rather time consuming. Hence, a good starting point of the process is necessary. Here, this point is given as the optimum of the static FEA model.

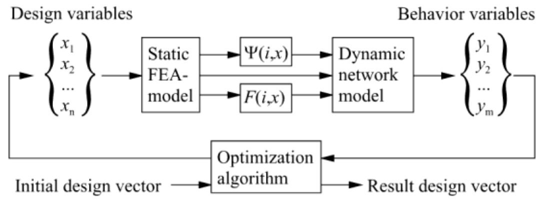

Figure 7. Data flow for the system dynamics optimization

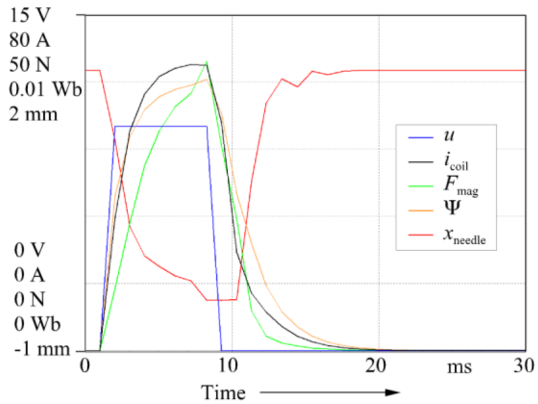

Figure 8. Nominal optimization based on the dynamic system model, optimum operating cycle

Figure 7 gives a schematic of the data flow controlled by OptiY. The optimization itself uses gradient-based algorithms again. It converges after about 500 steps. Figure 8 illustrates the calculated optimum operating cycle by the simulation of system variables over time. In our example, a cycle time of 1.8 ms is achieved.

4. Robustness Analysis and Robust Optimization of the Actuator

Designs found by nominal optimization, do not consider possible variances from nominal values of the system parameters, loads or ambient conditions. Therefore, such optimized designs show low resistibility and they are more sensitive to uncertainties. It is a main problem that optimization using nominal values of the design variables leads to non-robust solutions. One reason for this undesired effect is that designs having an optimum performance are typically determined by constraints.

The principle of robust design optimization is shown in Figure 9. The design with the nominal value a of x_1 leads to unacceptable values of y. For a more robust design, x_1 is moved from a to *b* and a lower failure probability and a smaller scattering of the variable *y* is achieved as well. In our example, we analyzed the probability of a system malfunction and then performed a robust design optimization.

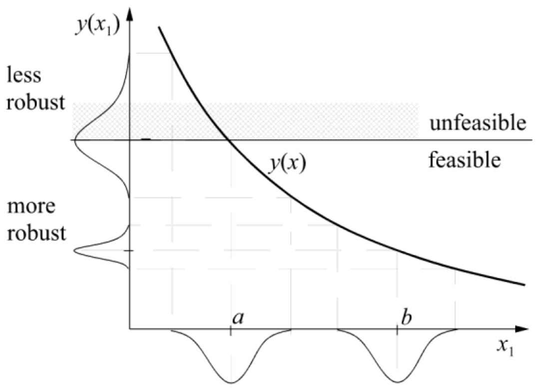

Figure 9. Principle of robust design optimization (RDO)

4.1 Probabilistic Analysis

A robustness analysis computes the probability density functions of the variables describing the system function from the density functions of the design, loads and ambient conditions. The static as well as the dynamic model, both are suitable to robustness analysis.

Concerning the dynamic model, we focused on scattering of the supply voltage u_0, and two design parameters, the starting point of the needle $x_{0\mathrm{needle}}$ and a specific diameter of the actuator d_{Magnet} as an example. Uniform distribution of u_0 and normal distribution of $x_{0\mathrm{needle}}$ and d_{Magnet} are assumed. In practice, it is a serious problem providing this information.

Figure 10 shows the resulting density functions of the system function (paper embossed or not) and of the cycle time. It can be seen that the system would not work with a probability of about 80 % at the nominal optimum.

We used Latin-Hypercube sampling (LHS) around the point of the nominal optimum. Alternatively, other DoE methods can be used. Response surfaces (in this case third order polynoms) were derived from the sampling results. This allows to use Monte-Carlo simulations (e. g. LHS) with a large sample size (100,000) to calculate the density functions of the system behavior. These methods are provided by the OptiY tool. A robustness analysis also revealed the size of influence of the variables on the system behavior.

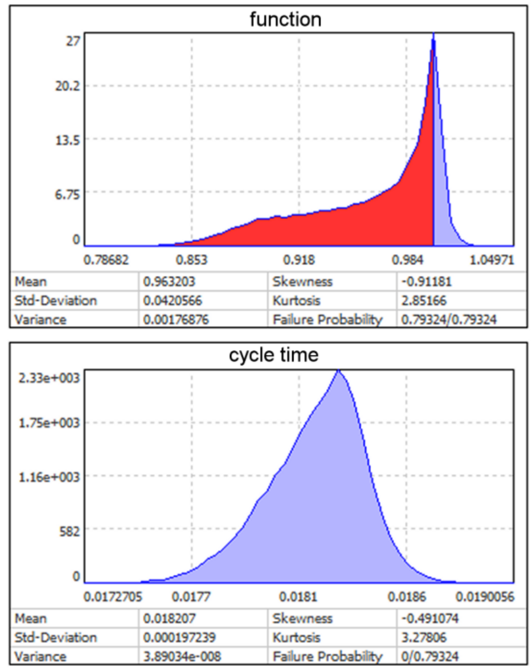

Figure 10. Probability density functions of the system function and the cycle time at the nominal optimum; red area stands for malfunction

4.2 Robust Design Optimization

The aim of the robust optimization is a design which guarantees higher reliability and lower scattering of the function than that found in the nominal optimum.

In order to reduce the computational effort we used the response surfaces instead of the system model. However, they are valid only in the parameter space they are computed for. Therefore, they limit the parameter space for the robust optimization. Figure 11 shows the probability functions at the robust design point with the minimum failure probability found on the response surfaces. As a result, the probability of a malfunction falls to about 7 %.

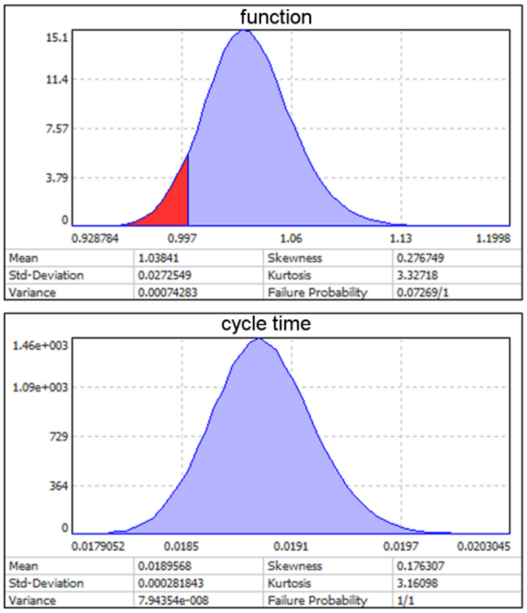

Figure 11. Probability density functions at a robust design point; red area stands for malfunction

5. Summary and Conclusions

By means of a magnetic actuator of a Braille printer it was exemplarily shown that algorithmic design optimization can be performed based on a dynamic network model that includes look-up tables computed from a static FEA model. The look-up tables were computed in each iteration step of the optimization according to the change in the design. Starting from a preliminary design we obtained an optimum design for a defined set of requirements. The optimization algorithm can also handle design variables that are given in form of distribution functions. That enables finding of the robust optimum with regard to the manufacturing tolerances. The final design meets our requirements regarding system function as well as reliability, considering the stochastic deviations of design parameters and ambient conditions.

The effort to merge the different simulation systems inside of the optimization tool OptiY is low. All computations were done on a quad-core PC running Windows. The presented methodology can be applied to many similar design optimization processes.

6. References

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7. Acknowledgements

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