# Genetic Algorithm Based Multi-Objective Optimization of Electromagnetic Components Using COMSOL® and MATLAB®

A. Subbiah*, O. Laldin
Faraday Future, Inc.
*Corresponding author: 18455 S Figueroa St, Gardena, CA 90248, anandakumar.subbiah@ff.com

**Abstract:** Design optimization of electromagnetic devices such as motors, inductors and actuators is multi-objective in nature, and aims to minimize cost, losses, and volume while concurrently maximizing power capability, reliability, etc. Classical optimization techniques, when used in such design problems, tend to converge to locally optimum solutions, which are highly dependent on the chosen initial conditions. A framework consisting of a genetic algorithm – a global optimization technique – coupled with the finite element method, requiring reasonable computational effort, is set forth in this paper to address a multi-objective design problem. An electromagnetic actuator is designed utilizing the developed framework by generating the trade-off between competing objectives.

**Keywords:** Genetic algorithms, multi-objective optimization, computational electromagnetics.

## 1. Introduction

The global energy infrastructure is comprised of a variety of power magnetic devices (PMDs) which include motors, generators, transformers, inductors, actuators, relays, etc. In the field of power engineering, and particularly in the design of PMDs, modern advances are targeted at reducing system losses, mass, volume, and cost, while simultaneously increasing power capability, reliability, and large-scale manufacturability. Achieving these competing objectives in modern applications requires advanced methods for optimal design of PMDs. These include computationally efficient device models in conjunction with state-of-the-art global optimization techniques.

The performance of classical gradient-bsaed techniques, which include gradient descent, Levenberg-Marquardt, simplex, method of moving asymptotes (MMA), ε-constraint methods [1], and so forth is subject to 1) convergence to local minima where the gradient approaches 0, 2) instability due to discontinuity or non-existence of the first or second derivatives, and 3) inaccuracy due to nonlinear and non-convex nature of the objective functions. Genetic algorithms (GA) [2] are a robust class of global optimization methods that circumvent these issues, and are used herein to address a multi-objective design optimization problem.

Another key component in the process is a high-fidelity electromagnetic (EM) model of a PMD. It is possible to develop various types of models for these devices, requiring increasing levels of computational effort, resulting in improved accuracy. The highest of these is typically obtained from a finite element (FE) model. In contrast, magnetic equivalent circuits (MEC) [3,4] can achieve relatively high fidelity and at a significantly reduced computational cost. However, the development and validation of these model for a given PMD topology is time-consuming, inhibiting rapid evaluation of novel architectures. Herein, an FE-based approach is used and shown to be in reasonable agreement with an MEC-based approach.

An EI-core actuator is designed to obtain the trade-off between competing volume and loss objectives. The actuator is shown in Figure 1, and is made of a stationary E-core wrapped with a coil of conducting wire and a movable I-core. The design parameters are the geometrical dimensions shown, winding parameters, and material types. The parameters and their respective ranges constitute the design space and are tabulated in Table A-1 of the Appendix.

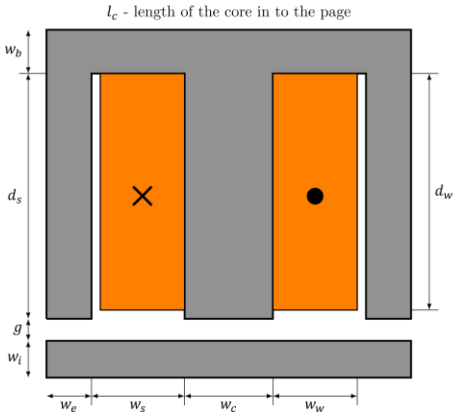


**Figure 1**. An EI-core electromagnet.

The actuator to be optimized is required to produce an electromagnetic force of 2500 N, meet certain design constraints while simultaneously minimizing volume and losses. It is noted that only resistive losses in the winding are considered. The design constraints are listed in Table 1. Most are readily evaluated directly from input parameters [4]; however, the current density constraint and the electromagnetic force are evaluated from the outputs of the FE model.

**Table 1:** Actuator design specifications.

| Specification | Value |
|---|---|
| Electromagnetic force | > 2500 N |
| Current density | < 7 A/mm$^2$ |
| Current | < 5 A |
| Volume | < 1 L |
| Packing factor | < 0.7 |

## 2. Methodology

The 10 design parameters and their respective ranges result in a large design space over which to optimize. In addition to the robustness of the GA to numerically challenging objective functions, it is capable of globally optimizing over such a design space given the availability of a computationally efficient model. Herein, an optimization framework is set forth with a MATLAB implementation of a GA (GOSET) [2] used in conjunction with an FE model implemented in the COMSOL AC/DC module, as shown in Figure 2.

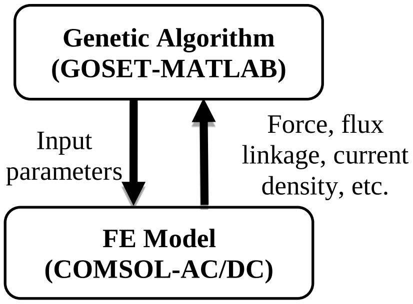


**Figure 2**. Overview of computation methodology.

The input to the GA are the design parameters, constraints, and objectives that need to be maximized (convertible to minimization problem). Typically, a tradeoff between competing objectives, referred to as Pareto-optimal front, is obtained at the end of the evolution process. The GA calls a fitness function in MATLAB, wherein all the constraints are checked and objective values computed. This function provides the COMSOL AC/DC module with geometry, material, and winding parameters via the LiveLink for MATLAB. The AC/DC modules evaluates the electromagnetic (EM) field solution, returning the resulting electromagnetic force, flux linkage, current density, etc.

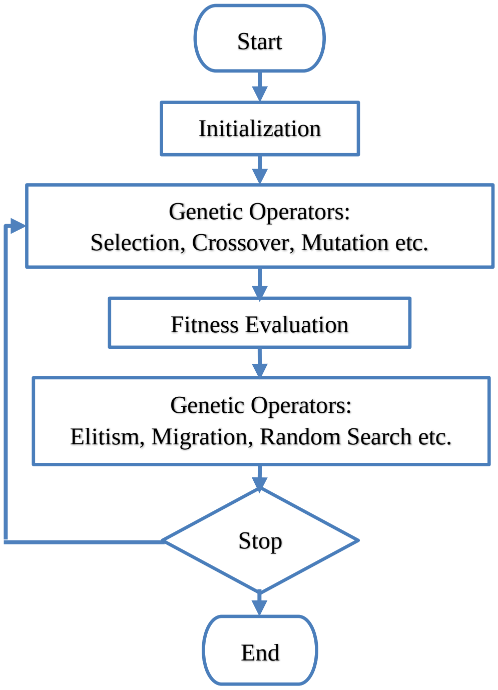


**Figure 3**. Execution flow chart of GA [2].

A brief overview of the execution of GOSET [2] is shown as a flowchart in Figure 3. The parameters from the design space are encoded as genes in a chromosome of a given individual. A random initial population of individuals is generated and fitness values are evaluated in the Initialization stage. Once the population is initialized, operators such as crossover, mutation and selection are used to modify the genes of the current generation to emulate natural reproduction and evolution.

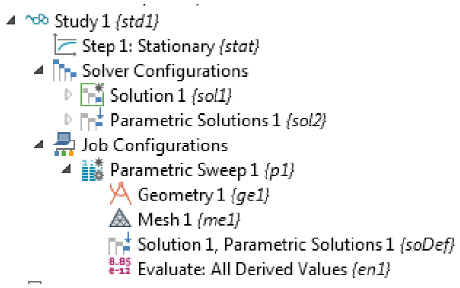
The fitness evaluation stage is then conducted, and is the most computationally expensive component of the design process. An initial set of constraints, not requiring an EM field solution, is first evaluated. If successful, the FE model is solved and the field solution obtained, from which the remaining constraints and objective values are evaluated. Thus, the computational effort is minimized.

Subsequently, advanced genetic operators are used to keep the best individual (elitism), redistribute the individuals between groups (migration), and explore other possible designs (random search) in the next generation. This iteration is repeated until the specified number of generation is reached.

## 3. Use of COMSOL Multiphysics®

The COMSOL products used in this paper include AC/DC and LiveLink for MATLAB modules. A parametrized COMSOL model for the actuator is created, using design parameters from Table 1. The fitness evaluation in the GA uses the LiveLink for MATLAB module to set the relevant model parameters. The steel and conductor types need to be changed based on the materials being chosen. This is in contrast with the Material Sweep option wherein all possible combinations of material types are simulated. The parametrized magnetic material change is achieved in two steps. The B($H$) and H($B$) functions of different materials are defined as global parameters, which are then used to obtain a vector product with a series of Kronecker delta functions. Piecewise functions are used to define constant properties for the various materials.

A parametric sweep is configured, as shown in Figure 4, to perform multiple EM solves for different parameter sets as from the GA. Doing so facilitates multiple stationary analyses for different geometry parameters, meshes, and coil current. Once the parametric sweep study is completed, the evaluated tables are transferred to the MATLAB workspace.

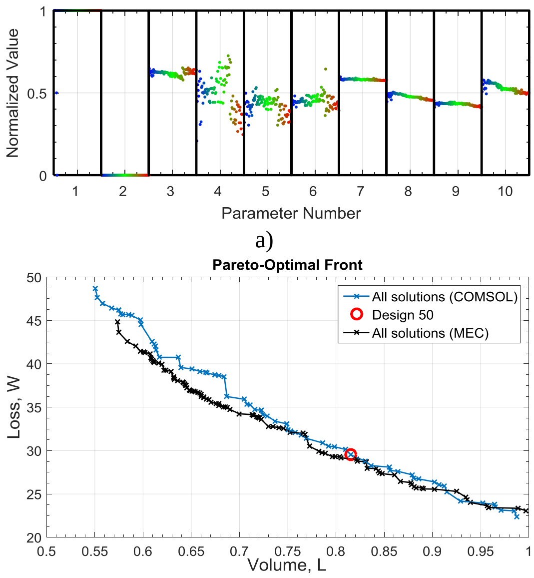


- Study 1 *{std1}*
  - Step 1: Stationary *{stat}*
  - Solver Configurations
    - Solution 1 *{sol1}*
    - Parametric Solutions 1 *{sol2}*
  - Job Configurations
    - Parametric Sweep 1 *{p1}*
      - Geometry 1 *{ge1}*
      - Mesh 1 *{me1}*
      - Solution 1, Parametric Solutions 1 *{soDef}*
      - Evaluate: All Derived Values *{en1}*

**Figure 4**. The Parametric Sweep job configuration.

## 4. Results

The GA is initialized with 200 population members and is run for 200 generations. The optimization process takes approximately 30 hours on a computer containing 24 CPU cores, clocked at 2.5 GHz, and 128 GB RAM. For a typical optimization run, the gene distribution and Pareto-optimal front is shown in Figure 4.



a)

b)

**Figure 4**. Results for a typical optimization run, including a) the gene distribution and b) the Pareto-optimal fronts.

In Figure 4a, parameters 1 and 2 represent discreet material identifiers, which converge to integer values that correspond to HyperCo50 steel and a copper conductor, respectively. These are therefore optimum material choices for the actuator. The remaining parameters are continuous values and are related to the geometry and winding of the actuator. Parameters 4 to 6 are distributed over a moderate range, with the I-core, end-leg, and base widths (i.e. $w_i$, $w_e$, and $w_b$, respectively) are typically less than half of the center-leg width (i.e. $w_c$), which itself tends to converge to a preferred value. In addition, there is convergence in the winding-related parameters (i.e. 7 to 10) suggesting preferred conductor counts and winding dimensions.

The Pareto-optimal fronts, obtained from both MEC- and FE-based approaches, are shown in Figure 4b; the similarity of the fronts implies that the proposed framework produces reliable results. Furthermore, the fronts themselves indicate the trade-off between competing objectives (i.e. volume and loss). With either approach, a family of designs (containing approximately 70 optimal choices) is available for consideration based on system-level requirements. However, the FE-based approach is expected to yield higher-accuracy results, and is more generic with respect to geometry, allowing for rapid investigation of novel architectures.

In Figure 4b, Design 50 from the FE-based approach is indicated, for which the EM field solution is provided in Figure 5. The actuator produces a force of 2519 N, drawing a current of 2.46 A. The winding packing factor is 0.699 and the current density is 3 A/mm$^2$. The loss and volume of the actuator are 29.54 W and 0.81 L, respectively. The design satisfies all the outlined specifications, the parameters for which are tabulated in Table A-1.

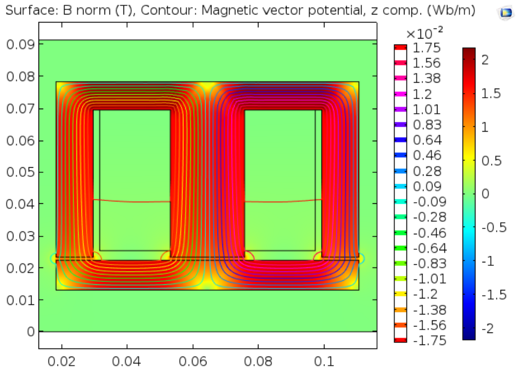


**Figure 5**. The B-field and vector potential iso-contour plots for Design 50.

## 5. Conclusion

A multi-objective design of an actuator using a framework of COMSOL and MATLAB/GOSET is presented. The Pareto-optimal front obtained using the framework agrees well with that obtained from the MEC-based design optimization, establishing the validity and reliability of the approach. The results of a design are presented and are observed to satisfy the specified requirements. The methodology presented herein is sufficiently general to be expanded to a variety of PMD applications.

## 6. References

1. E. K. P. Chong and S. H. Żak, *An Introduction to Optimization*, John Wiley & Sons, New York (2013).
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4. S. D. Sudhoff, *Power Magnetic Devices: A Multi-Objective Design Approach*, 154-177, John Wiley & Sons, New York (2014).

# Appendix

**Table A-1:** Design space and parameter values for Design 50 (FE-based approach).

| Parameter | Symbol | Description | Range |  | Design 50 |
|---|---|---|---|---|---|
|  |  |  | Min. | Max. |  |
| 1 | $T_{cr}$ | Steel core material | 1 | 5 | Hiperco50 |
| 2 | $T_{cd}$ | Conductor material | 1 | 2 | Copper |
| 3 | $w_c$ | Width of the core center | $2\times10^{-3}$ | $10^{-1}$ | 2.26 cm |
| 4 | $\frac{2w_e}{w_c}$ | Twice end-leg to center core width ratio | 0.5 | 1.5 | 1.00 |
| 5 | $\frac{2w_i}{w_c}$ | Twice I-core to center core width ratio | 0.25 | 1.5 | 0.826 |
| 6 | $\frac{2w_b}{w_c}$ | Twice E-core base to center core width ratio | 0.25 | 1.5 | 0.784 |
| 7 | $a_c$ | Desired cross-sectional conductor area | $10^{-9}$ | $10^{-4}$ | 0.826 mm$^2$ |
| 8 | $N$ | Desired no. of turns | 1 | $10^3$ | 804 |
| 9 | $N_w$ | Desired slot width in conductors | 1 | $10^3$ | 20.2 |
| 10 | $N_d$ | Desired slot depth in conductors | 1 | $10^3$ | 41.2 |