Modelling and Optimization of the Magnetic Circuit of a Mobile Nuclear Magnetic Resonance Device for Magnetic Resonance Imaging

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ABSTRACT

This paper presents the genetically optimized magnetic circuit of a Mobile Universal Surface Explorer (MOUSE) for magnetic resonance imaging. By genetic optimization of several Finite Element models of the MOUSE a suitable solution can be found which meets the requirements of linear field homogeneity and sufficient field strength for MRI applications.

I. INTRODUCTION

Magnetic resonance imaging, commonly known as MRI, is a powerful non–invasive imaging technique in clinical practice and material science. Unlike x–ray based computed tomography (CT), MRI doesn't use ionizing radiation and hence is considered safe. The resolution of MRI basically depends on the homogeneity and field strength of the primary magnetic field B_0 over the volume of interest. In clinical tomographs homogeneous fields are produced by solenoid coil windings with high current excitation. Those high currents require active shielding of the stray fields and helium cooling of the equipment. These solutions are unsuitable for mobile usage because of costs and especially weight. This paper introduces an optimized magnetic circuit for a Mobile Universal Surface Explorer called MOUSE which meets the requirements of sufficient homogeneity and low weight and costs.

a. Design of the NMR–MOUSE

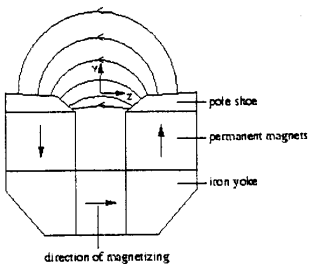

Fig. 1: Principle C-core design of the MOUSE

For mobile usage the essential B_0 flux density can be produced by highly remanent magnets as NdFeB. The homogeneity shall be influenced by the MOUSE' geometrical shape. The basic shape must follow the design of a C–core. In addition to a static B_0 field, MRI sensitive samples need excitation by an externally applied high frequency field B_1. B_0 and B_1 are expected to be perpendicular to each other. An analytical solution of this field problem is hardly possible. So one must think of an intelligent empirical Finite Element examination of the arrangement. The use of optimization techniques presents itself. A gradient based tool is implemented in the commercial FEM software ANSYS. A first prototype of the MOUSE has been built according to three dimensional ANSYS static field solutions with vector potential formulation and far field conditions in order to consider the amount of surrounding air. Figure 1 shows the principle C–core design of the MOUSE whereas figure 2 presents the constructed prototype consisting of magnetic material NdFeB 340/88 with a magnetic remanence flux density of B_R=1.33 T and permeability • $_R$=1.3296 with B_0=260 mT at the surface of the MOUSE and a decrease of 1.25 T/m in y–direction which is the penetration depth of the examined sample. The prototype was built by Thyssen Magnettechnik GmbH, Dortmund, Germany. A detailed description of the MOUSE can be found in [1].

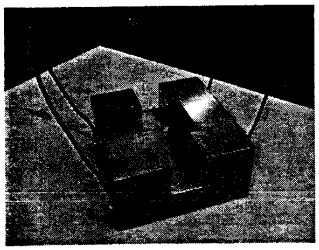

Fig. 2: Prototype of the MOUSE

b. Genetic optimization of the MOUSE

Solution of the MOUSE problem by a gradient technique leads to very fast convergence of the FEM computation. Expanded examinations of different design sets are prevented. So an optimization tool based on genetic strategies was implemented. During the evolution process, the genetic algorithm uses more efficiently the provided search domain depending on population diversity and selective pressure [2]. Chromosomes present feasible designs of the MOUSE and are evaluated by the optimizer. Strong design sets which deliver the best results for the approximation of the object function are allowed to mutate and bequeath the specific characteristics of their shape. The chosen cost function takes into account the deviation of the computed and the desired field as well as the preferred weight of the MOUSE design.

$$\varepsilon(\underline{x}) = \iiint \left| B_{0_i}^{FEM} - B_0^{desired} \right|^2 \cdot W(\underline{x}) dV + \frac{w_i^{FEM}}{w^{desired}} \quad (1)$$

Fig. 3: Object function of the genetic MOUSE problem

II. OBJECT–ORIENTED IMPLEMENTATION

The genetic optimizer is implemented in an object–oriented environment. By using object–oriented paradigms it is possible to design classes which realize genes, chromosomes and populations. The object–oriented approach submits the simple extension of different genetic algorithms which work on data structures for genes, chromosomes and populations. The use of float point arithmetic instead of regular binary coding reduces the binary disadvantages regarding large search domains which may result in poor convergence. Advanced strategies like multi search domain optimization strengthen the effect of fine local tuning. The complete optimization has been developed in C++ and successfully applied to multidimensional test functions and the optimization task of gradient coil development for nuclear magnetic resonance devices [3], [4]. Because of the computational expense for three dimensional FE calculations, the optimization is limited to 2D calculations.

III. OPTIMIZATION RESULTS

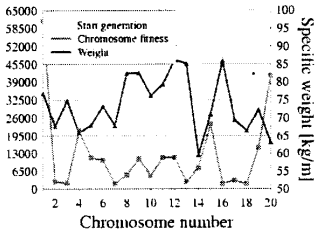

Fig. 4: Fitness distribution at the beginning of the optimization

Figures 4 and 5 demonstrate the fitness distribution at the beginning and at the end of the optimization after 30 iteration steps. The maximum value of the chromosome fitness could be reduced about 100 times that of the start value. The optimization effect becomes more obvious by considering the fitness distribution of the best chromosome of each generation as a function of the iteration step. The optimization progress at the beginning is fairly strong and results in a fast minimization of the object function 1. This means a good approximation of the desired field distribution by the computed one for the actual MOUSE design. By the way, a reduction of the MOUSE weight also takes place. Figures 7 to 18 present the alteration of the MOUSE shape and the corresponding B_0 distribution during the optimization. After 30 generations a feasible design set was found which fulfils the requirements of a low field decay in direction of the MOUSE' penetration depth and a low weight.

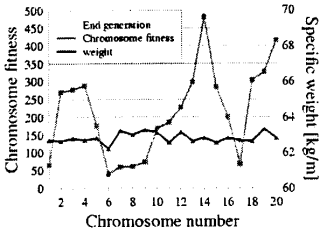

Fig. 5: Fitness distribution at the end of the optimization

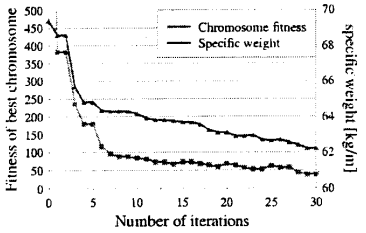

Fig. 6: Optimization progress of the best chromosome

In contrast to the conventionally designed NMR–MOUSE [1] the randomised shape of the genetic MOUSE is obvious which effects the pole shoe form as well as the shape and magnetization direction of the vertical magnet.

IV. CONCLUSION

In this paper the powerful application of genetic algorithms in combination with Finite Element computations for the optimization task of the magnetic circuit of a mobile magnetic resonance device has been presented. The genetic optimization affords different shapes from those found by simple parameter variation of the unknown design variables. It is proven that stochastic algorithms like genetic ones are not only limited to the solving of analytic equations. They can be linked to FEM problems which are of major engineering interest. The limiting factor is the computational expense for the FEM calculation. The application of object–oriented design methods simplify the development of such a complex optimization tool and the connection to the actual problem.

V. REFERENCES

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[2] Z. Michalewicz, *Genetic Algorithms + Data Structures = Evolution Programs*, Springer, New York (1999).

[3] H. Popella, "Genetic Algorithms for two dimensional Design Optimization of a Magnetic Resonance Device", *International Journal of Applied Electromagnetics and Mechanics*, vol. 15, pp. 219–223.

[4] H. Popella, "Genetic Optimization of Planar Gradient Coil Systems for a Mobile Magnetic Resonance Device Using Object–Oriented Design Techniques", in *Proceedings 2001 OOPSLA*.

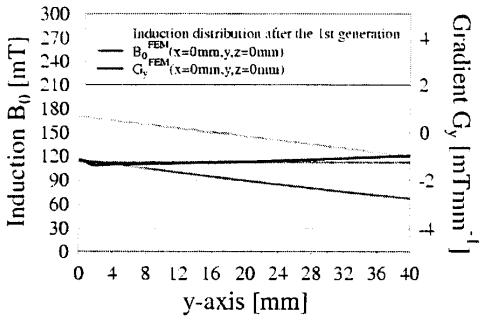

Fig. 7: Induction distribution after the 1st generation

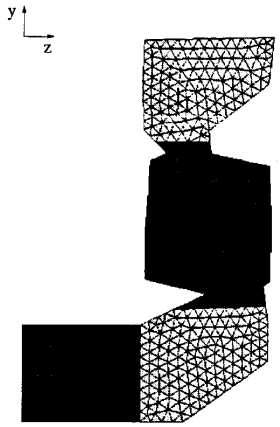

Fig. 8: MOUSE shape after the 1st generation

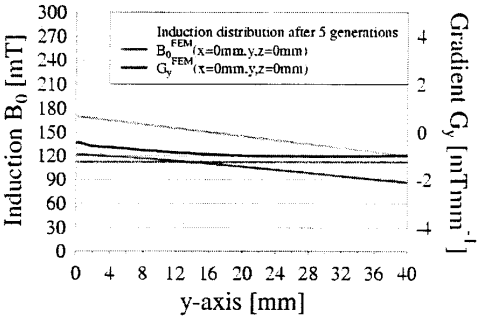

Fig. 9: Induction distribution after the 5th generation

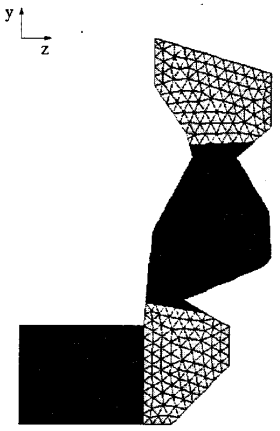

Fig. 10: MOUSE shape after the 5th generation

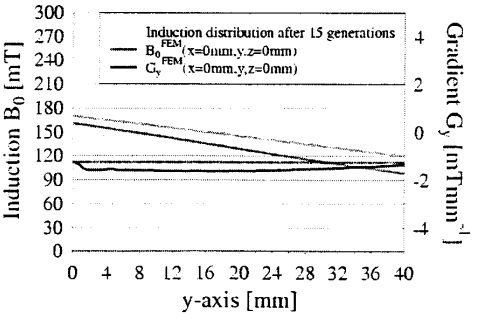

Fig. 11: Induction distribution after the 15th generation

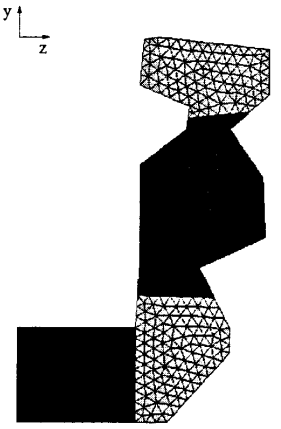

Fig. 12: MOUSE shape after the 15th generation

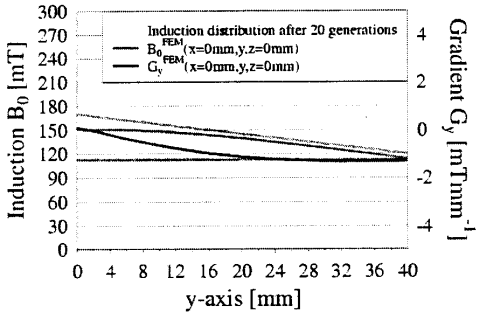

Fig. 13: Induction distribution after the 20th generation

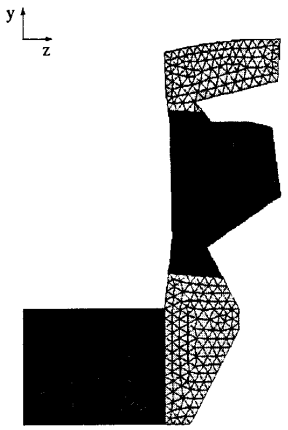

Fig. 14: MOUSE shape after the 20th generation

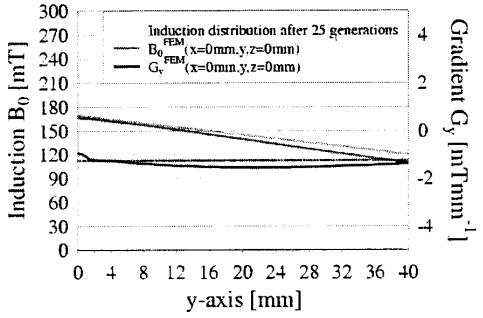

Fig. 15: Induction distribution after the 25th generation

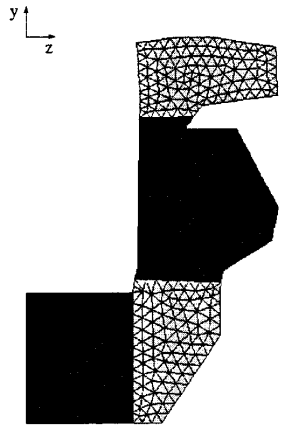

Fig. 16: MOUSE shape after the 25th generation

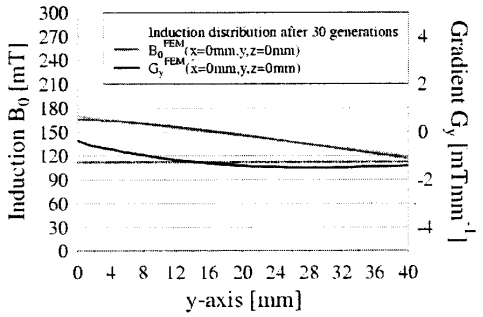

Fig. 17: Induction distribution after the 30th generation

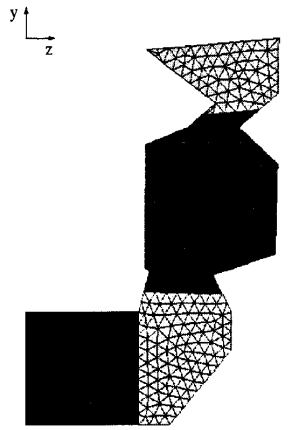

Fig. 18: MOUSE shape after the 30th generation