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FINITE ELEMENT BASED GENETIC ALGORITHM FOR STRUCTURAL DESIGN OPTIMIZATION

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ABSTRACT
Genetic algorithms are nowadays widely used in various manufacturing problems dealing with optimization. While most optimization tasks need a certain form of model that defines the optimization's figure of merit or the objective function, such objective function for some phases in the manufacturing process, such as design, is difficult to establish using conventional techniques. On the other hand, current design models in 3D are in most cases integrated with finite element analysis tools that generate finite element meshes giving the complete mathematical description of the physical model using nodal values and shape functions. The aim of this article is to point out the general scheme associated with the implementation of finite element descriptions in optimization of structural design using global optimization capability of genetic algorithms.
Keywords: Finite element analysis, genetic algorithm, design optimization

1. INTRODUCTION
Achieving a safe and economical design is the primary goal of any designer of mechanical structures. While safe design is mostly dictated by a set of accepted national/international design codes, economical design of structures requires a systematic formulation of the design problem as an optimization problem and solving it by one of the existing optimization techniques. By the concept design optimization, we mean seeking a design configuration that meets all specified requirements with a compromise of certain factors such as weight, surface area, volume, stress, cost, etc. The optimum design is one that is as effective as possible with respect to the influencing factors. Particularly, design optimization problems involve varying some parameters of the model that lead to improvements in terms of mechanical behaviors such as reduced effect of stress concentration factors, reduced weights, increased stiffness and stability, etc.
The area of structural design optimization has been and continues to be an active area of research. Previously, several mathematical programming techniques such as numerical approximations and linear programming techniques have been widely studied. For example, Vanderplates [1] applied numerical approaches such as gradient method and approximation methods to the optimisation of structures. The earlier attempts of numerical optimization were based on Taylor series expansion of the objective functions and the constraints with respect to the design variables. As reported by Ali and his colleagues [2], the numerical methods built in some finite element analysis (FEA) such as ANSYS are based on transformation of the member forces of a non-linear structure to a linear system using Taylor series expansion. Though heavily studied, mathematical programming techniques gained insignificant practical applications in the design optimization due to the implementation difficulties, the need for derivatives and the deterministic and exhaustive nature of the technique.
Most recently implemented approaches include soft computing techniques such as the genetic algorithm (GA). These techniques have shown to be efficient over a wide range of engineering applications. Probably, the first attempt of using GA technique to structural optimization was reported

in a conference article presented by Goldenberg and Samtani [3] where a 10 bar truss problem was utilized to study the role of GA in structural optimization. On the other hand, optimization using GAs presupposes existence of some form of the objective function, which in many cases is difficult to establish.

This paper presents a preliminary study that indicates the possibilities and benefits of using numerical results from FEA models as the objective function of the optimization and establishing an integrated GA and FEA. The paper focuses only on the rationale for this implementation, and not in the extensive application due to the limitations on the number of pages for this conference paper.

2. BACKGROUNDS FOR PROBLEM FORMULATION

2.1. Genetic Algorithms

Genetic Algorithms are search tools with great versatility, easy implementation and ability to find global optimum solutions. The main principle of the technique was initially stated by Holland [4] as a search algorithm based on the mechanics of natural selection and natural genetics. Extended descriptions and applications of the GA technique in several of the engineering field are given in the literature elsewhere [2].

GAs have many advantages over traditional search methods. Apart from their powerful global search ability to find optimum solution, GAs are favored due to the fact that they do not need extensive data than information on the fitness function and the necessary constraints on the solution. As GAs are computational tools, they need a single figure of merit as a fitness function to perform optimization. In many engineering fields, however, there are certain processes that are not possible to describe using analytical models for GA optimization. Recent research interests in the application of this technique have focused on finding modified forms of the technique or obtaining assistance from other computational tools such as neural networks [5] so that the power of the GAs can be fully exploited. This paper is part of this effort where numerical data generated in the analysis model of FEA tools is utilized as input values, for the shape optimization of designs using GAs.

2.2. Optimization Techniques in Existing FEA Tools

FEA is a numerical method for analysis of complex engineering problems. The technique attempts to analyze the problem that is a continuous system by breaking it into discrete finite elements and approximating at nodal points. For each set of loading condition, the relevant set of equilibrium equations, compatibility conditions and material law are specified to determine the structural response such as stress state, strain and deflection, natural frequency etc.

To perform the required tasks, the FEA process should be executed through three main modules: *pre-processing*, *solution* and *post-processing*. Today’s commercial FEA tools have also an extra optimization module having limited capability. Current design models in 3D are in most cases integrated with finite element analysis tools that generate finite element meshes giving the complete mathematical description of the physical model using nodal values and shape functions.

One of the methods favored in existing FEA based optimization techniques is *design parameterization*. This characterizes the changes in dimensions and position of geometric control points that govern the shape of the structural boundary so that the design performance improves. Particularly in the modern dimension-driven CAD systems, the designer captures the design intent in the CAD model by specifying certain dimensional parameters and leaving others as dependant variables that are adjusted later in the design process. Many authors, for example Braibant and Fleury [6] and Chang and Choi [7], have reported this technique. This is specially favored in the feature based CAD tools where a library of design features including the shape parameters can be developed [8]. It permits not only relieving the designer from direct manipulation of the underlying geometry of the model, but also variation of design parameters and a dynamic change of the model geometry while preserving the basic shape of the design intent.

In existing FEA tools such as ANSYS, there are three categories of variables for design optimization.

- *Design variables*: the independent variables that directly affect the design objective such as the width and height of a beam.
- *State variables*: the dependent variables that change as a result of changing the design variables. These variables are necessary to define design constraints. For example, the

maximum allowable stress constrains the level of the optimum volume or cross-sectional area to be achieved.

- *Objective variables*: the variable(s) that need to be optimized (maximized or minimized).

  Though it is a well-known fact that achieving an optimized design is one of the main goals of the design process, insignificant progress has so far done to integrated the powerful optimization techniques such as GAs into existing design and analysis systems. As of today, for example in ANSYS, we find only two optimization methods, namely the subproblem approximation or zero-order method and the first order method. Both these methods are based on parameterization of the design variables.

3. THE PROPOSED APPROACH

Typical structural design involves large number of redundant parameters that make the optimization task very difficult on the basis of the designer's experience and intuition. There are many aspects of any design that are subjected to optimization including: dimensional parameters such as thickness, diameter, length, etc., placement of supports, natural frequencies, material properties, cost of fabrication and so on.

Figure 1 shows how these parameters and other post-processed analysis data are fed into the proposed GA-based optimization approach.

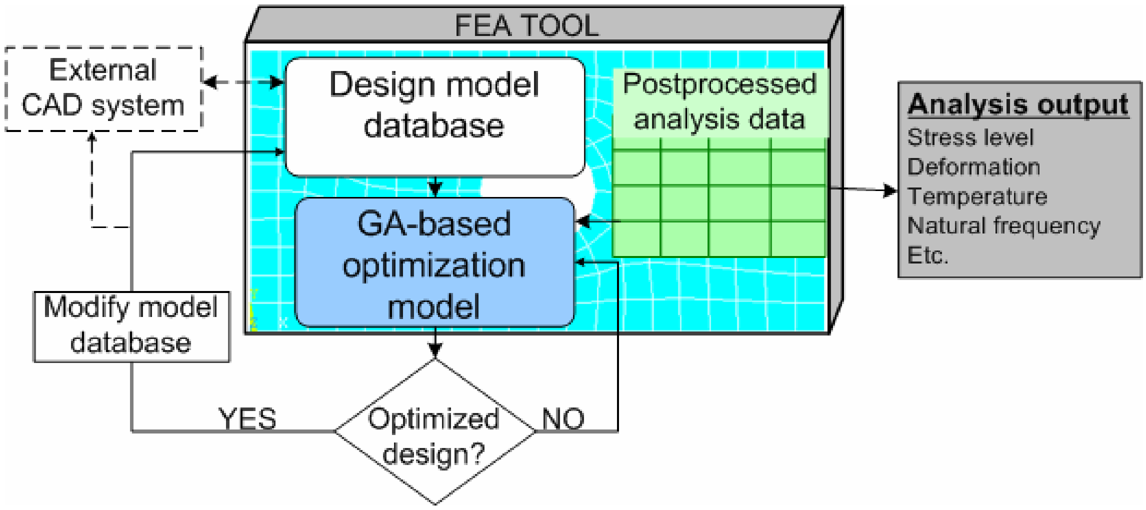

Figure 1: Scheme of a FE based genetic algorithm for shape optimization

Many optimization problems are formulated either as cost function or weight function. Since cost is not always directly varying with dimensions, design optimization is best formulated as a function of cross-sectional variables which directly reflect the volume and hence the weight of the structure. For example, in formulation of an elastic beam, the following variables can be defined for each finite element in the structure:

- *Independent variables*: thickness/width (t), span (L) and height (h) of the discrete element
- *Dependent variables*: cross-sectional area (A = t*h), Volume (V = t*h*L), area moment of inertia (I = t*h^3)/12, etc.

For each discrete or finite element in the structure, the shape optimization problem is then formulated as a shape that has minimum weight and stress concentration effect. The objective function is thus stated by

$$\min (W) = \sum_{i=1}^{NE} V_i \rho_i \qquad \ldots (1)$$

where V_i and ρ_i are volume and density of each finite element and NE is number of elements in the model.

Further, restriction on the structural analysis parameters such as stresses and deformations are expressed by the combination of the above-mentioned variables. For instance, for each node or Gauss point of a bar element, the equivalent (Von-Mises) stress σ_{eq} is calculated from

$$\sigma_{eq} = \sqrt{\sigma_x^2 + 3\tau_{xy}^2} \leq \sigma_{permitted} \quad \ldots (2)$$

Similar restrictions on deformation are defined where the displacement of each discrete element is described by interpolation functions of the nodal displacements.

4. CONCLUSION

This paper has attempted to highlight the possibilities and advantages of implementation a finite element based genetic algorithm to shape optimization of structures. The paper has focused on the general scheme of the ongoing study and presented the proposed approach to integrate the two tools. This has a dual benefit. Primarily, genetic algorithms need numerical figure of merit to perform an optimization task. This can be supplied from the post-processed data of FEA tools. On the other hand, FEA tools are approximation techniques where stresses and deformation are estimated using nodal values and interpolation function such as Langrange polynomials. In the course of this estimation process as well as while transforming the global continuous problem to discrete elements, errors are induced into the solving process. Further studies will focus on how GAs can assist to reduce such errors and improve the convergence and of the interpolation as well as the sensitivity of the results.

5. REFERENCES

[1]. Vanderplats, G.N. Numerical optimisation techniques for engineering design. McGraw-Hill Inc. 1984. Pp. 250-82.

[2]. Ali, N., Behidnan, K. and Fawaz, Z. *Applicability and viability of a GA based finite element analysis architecture for structural design optimization*, Computers & Structures, **81,** 2259 – 2271, 2003.

[3]. Goldenberg, D.E,, Samtani, M.P., Engineering Optimization via the Genetic Algorithm. In: *9th Conf. On Electronic Computation*, NY, ASCE, 1986, Pp. 471-82.

[4]. Holland, J.H., *Adaptationin Natural and Artificial Systems*, University of Michigan Press, 1975.

[5]. Gelgele, H.L. Solving Manufacturing System Problems Using Hybrid Genetic Algorithm and Neural Networks, *7th International Research/Expert Conference "Trends in the Development of Machinery and Associated Technology" TMT 2003*, Lloret de Mar, Spain, 15-17 Sept., 2003.

[6]. Briabant, V., and Fluery, C. Shape optimal design using B-splines, *Computer Method Applications in Mechanical Eng'g*, 1984, 44, Pp. 247-267.

[7]. Chang, K.H. and Choi, K.K., A geometry based parameterization method for shape design of elastic solids, *Mech Struct Mach* 1992, **20** (2) 215-252.

[8]. Botkin, M.E., Shape design modeling using fully automatic three-dimensional mesh generation. *Finite Elements Anal*, Des 1991, 10: 165-181.