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Methodology

APPLICATIONS OF GENETIC ALGORITHMS IN OPTIMAL TRUSS DESIGN

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Abstract

Current approaches to truss optimization are usually directed toward minimizing the weight of a given topology or form. They are not typically able to suggest new topologies or deal with a wider range of design constraints which may be difficult to define as differentiable functions, but do affect economic efficiency. These include fabrication costs that consider complexity and waste of material, discrete member sizes with stress capacities that vary with size, effects of connections, or nonlinear conditions of stability. Genetic Algorithms (GAs) can be used to solve complex optimization problems including the determination of optimal topologies. In this paper I show that GAs can be used to optimize trussed structures for weight, and discuss how the method could be expanded to enable the inclusion of a wider range of optimization parameters including the selection of optimal topologies. I have shown an example which uses a GA to determine the optimal geometry of a nine member truss. The procedure used by the GA in the solution is described, and results are shown. A procedure for topology optimization is described.

1. Introduction

Examples of the structural optimization of trusses are readily found in the literature using mathematical methods. These solutions generally divide into three groups: 1. optimization of member shapes, 2. optimization of truss geometry and 3. optimization of truss topology. Solutions which use standard material properties and commercially available shapes are generally more complex to derive. In addition, geometry optimization usually incorporates member optimization, and topology optimization incorporates both member and geometry optimization. This makes the latter types of optimization progressively more complex. When seeking an economic optimization (as opposed to purely material optimization) further considerations are required. These might include: available lengths and sections of members, connection types and number, limits of fabrication and transportation, losses due to waste, and critical load cases. More recently, methods employing Genetic Algorithms (GAs) have been used for solving structural optimization problems (Coello, 1994) (Hajela, 1993). GAs offer advantages in solving problems which contain complex, discontinuous and hard to define functions. They are, therefore, well suited for the type of discrete optimization problem described so far, with commercial materials and sizes. This paper describes a method used by the author for geometric optimization and gives results from an example of a nine member simple span truss. An extension of this method is proposed, which is currently still in development, for the optimization of topology as well as geometry.

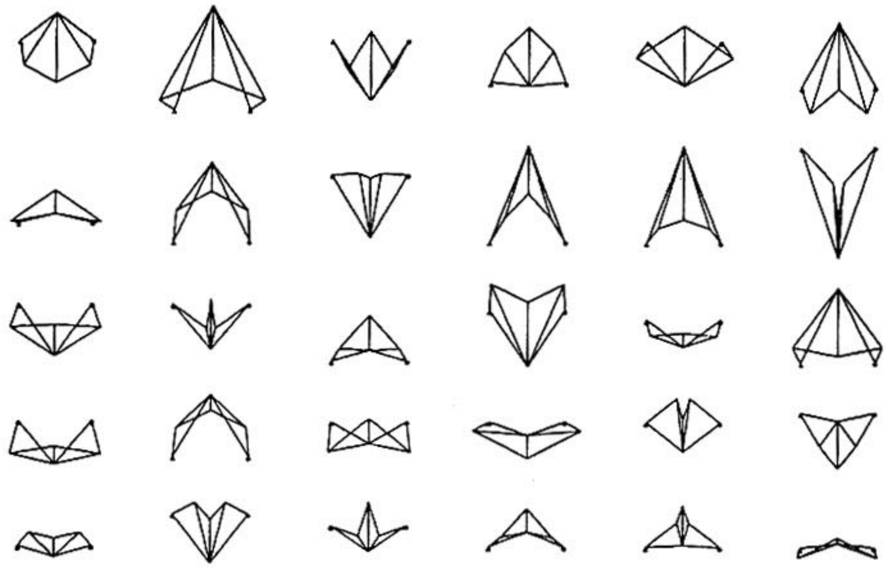


Fig. 1. Examples of Randomly Generated Trusses.

2. Procedure for Geometry Optimization

The concept of searching for problem solutions using techniques patterned after genetic inheritance was developed in the seventies by Ingo Rechenberg in Germany (Rechenberg, 1973) and by John Holland in the United States (Holland, 1975). Since that time much activity on both sides of the Atlantic has led to several variations of the basic approaches. This work uses a GA patterned after the CHC method developed at Philips Laboratories by Larry Eshelman (Eshelman, 1991). It has the advantage of being able to work with relatively small populations of 50 individuals per generation, and still succeed over a wide range of problems.

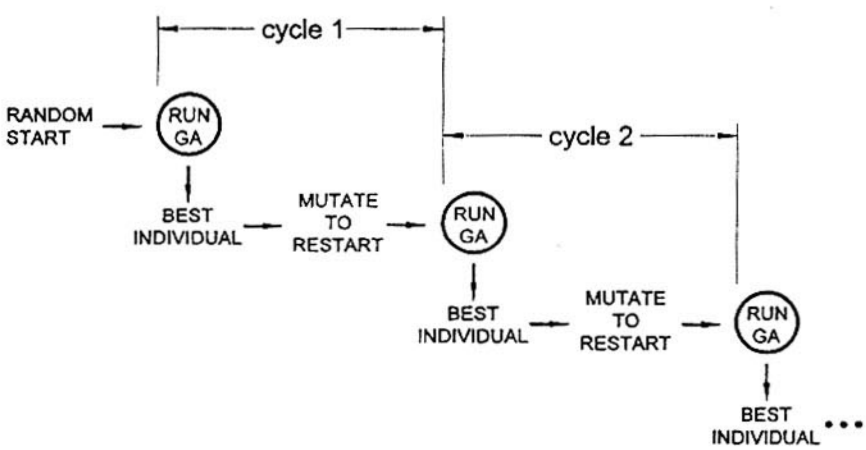


Fig. 2. Overall Plan Used in the CHC Method.

In general, GAs operate on an entire population of individuals (in this example trusses) at a time. The problem is characterized in terms of "genes" which can be altered by genetic mechanisms, such as mutation or crossover, to produce new individuals which compete for survival. A fitness function (the truss weight in this example) determines how an individual is ranked in the population. The poorer solutions die out naturally, while the population "evolves" toward the better solutions. Because of the randomness in both mutation and in attribute crossover between individuals the possible field of solutions is well and efficiently explored to find the best solution overall. In the CHC method, the search for the best solution proceeds in a series of cycles each progressively becoming more focused on a particular solution.

Figures 2. through 4. describe the procedure used in a CHC GA. Using the simple roof truss as an example, the procedure begins with the random generation of a set of solutions. The solutions are deliberately allowed as much freedom as possible. If the GA is working correctly, undesirable solutions will die out naturally. Therefore, the truss is allowed as much geometric freedom as will still allow it to be analyzed as a truss (kinematicly stabile). Members can invert, cross other members or even extend beyond the supports. Figure 1. shows examples of randomly generated individuals. In every case the loading is of the same type, a uniformly distributed downward load, converted to point loads on the joints.

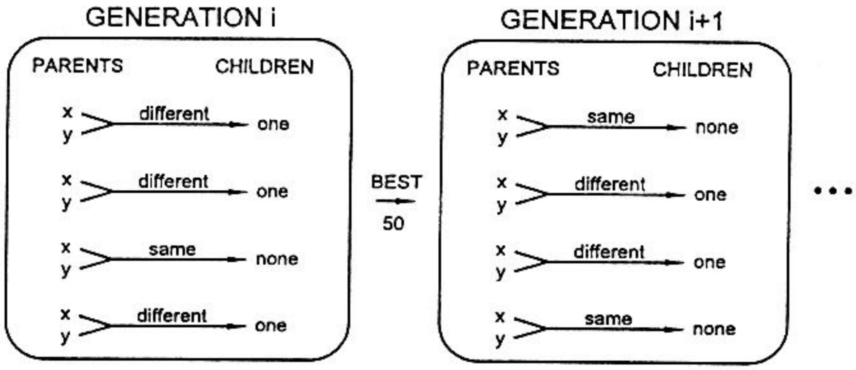


Fig. 3. Adaptive Plan for the GA.

The process continues by iterating a set of rules which make up the GA. In Figure 2. the sequence of "run GA - choose best - mutate to restart" describes the overall cycle of steps toward optimization. The GA procedure, described in Figure 3., represents the successive breeding of a population in a number of generations. It contains several generations which gradually become more and more homogeneous, and ultimately yield one type as being superior. The production of children in a generation is dependent on the level of genetic difference of the paired parents. If a pair of parents are found too similar, no children will result. When the number of children resulting from the breeding procedure drops below a specified level, a sufficient level of homogeneity will have been reached, and the cycle is ended. At this point the best individual is chosen from the current population, and through mutation 49 new variant individuals are created, which together with the one best individual compose the next start population of 50 individuals. This is the "restart" in Figure 2. The cycle of "run GA - choose best-mutate and restart" continues until the results stabilize. In running these trials, 30 cycles were always used in order that convergence could be compared between runs. The solution usually converged much faster - usually in about six cycles.

Figure 4. shows a detailed view of the breeding procedure used by the GA. It results in the refinement of successive generations of individuals toward the fitness criteria (least weight). The 50 individuals of each generation are randomly paired as parents. Each pair of parents are then examined to insure that they are different before they are allowed to breed. If they are the same, there is no reason to breed them since any child would be identical to the parent, and no new solutions would be introduced into the population. After some number of generations the population will become homogeneous, and further breeding will not introduce any new individuals (solutions). When this condition is reached the cycle is ended. Figure 8. shows a typical generation's progression toward homogeneity. The children are actually produced by the crossover of gene attributes (joint coordinates) of the parents. Crossover is more conveniently performed with the genes represented in binary format. Figure 4. shows the crossover of joint coordinates in binary format to produce one child.

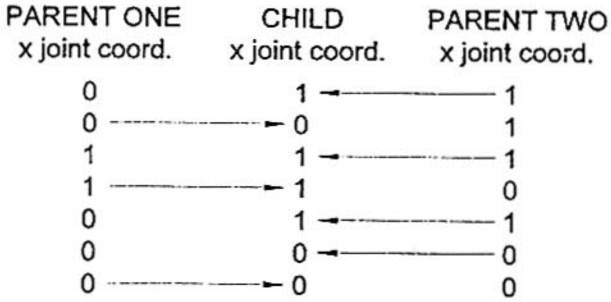
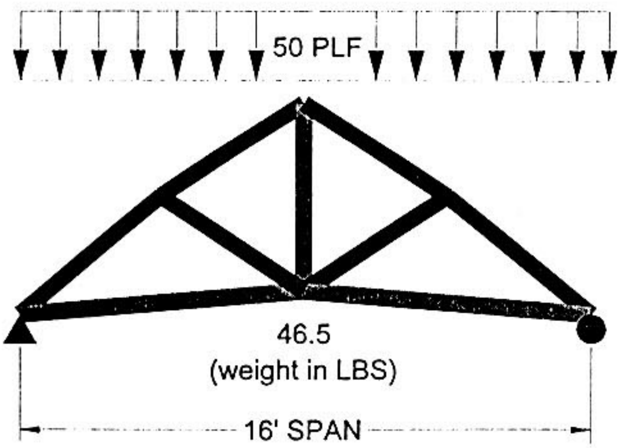


Fig. 4. Crossover of Binary Genes to Produce a Child.

Once a generation is established with both parents and children, all individuals are ranked by the fitness criteria. For the trusses this means each truss is analyzed, members designed, and a total weight calculated. The 50 lightest trusses taken from the combined population of parents and children, survive to be parents in the next generation, while the heavier examples die out. In this way successful patterns are perpetuated, and stabilize in the gene pool after some number of generations. For each pair of parents, a child is only allowed when the genetic material of the parents is shown to be sufficiently different. If a random pair of parents are found to be very similar no child is produced. But both parents (like all the other parents) do remain in the population themselves. This has the affect of hindering premature convergence by slowing the duplication of similar schema (sets of genes). As the generations continue, poorly performing attributes are gradually filtered out of the gene pool and the population becomes more homogeneous. At some point all the paired parents of a generation will be so similar that no children are produced. This situation signals the end of one GA cycle. A single best performer is chosen from this last generation. That best truss is then used to create a new "restart" population by a series of random mutations to its genetic code (joint coordinates). The resulting population is not entirely random like the very first start group, because it is based on the characteristics of the last best truss. This enables the next GA sequence to begin optimization using a more restricted range. With each successive cycle of "run GA - choose best - mutate and restart" the system becomes more centered on the correct area of the range of solutions.

3. Design Parameters Used

To simplify the initial coding of the program, the problem was kept deliberately as simple as possible while still maintaining the essential elements. The problem describes a commercial type wood roof truss. The design prescriptions and stress limits described in the National Design Specification for Wood Construction (NDS 1991) were followed including form and stability factors accounting for buckling of compression members. Member sizes were restricted to a set of eight standard U.S. sizes of dimensioned lumber typically used for this type of truss. The nominal dimensions were in inches: 2x3, 2x4, 2x5, 2x6, 2x7, 2x8, 2x10, 2x12, 2x14. Material properties were taken from the NDS Supplement for Douglas Fir So., Grade No. 2, with 19% Moisture Content. In simplifying the problem, all joints were considered pinned with no continuous members, and all loadings were applied at the joints. Only one load case was considered. It was a uniform gravity load of 50 PLF. The topology was predetermined as shown in Figure 5. Because the load was symetric, only symetric geometries were considered. An example of possible geometries can be seen in Figure 1. The range of possible geometries was allowed as much freedom as practical. In Figure 1. one can see the members were allowed to drop below and even overhang the supports. Members were even



- Follow all provisions of the National Design Specification for Wood Construction
- Use Douglas Fir So., Grade No.2, 19% M.C.
- Use standard dimensioned sizes
- Assume normal load duration

● Black signifies compression
● Grey signifies tension

Fig. 5. Design Parameters for Nine Member Truss.

allowed to cross over one another. Such impractical solutions, although allowed, did not prove successful, and thus died out of the population on their own, as is described below. The fitness function used to rank the relative merit of solutions, can potentally contain a list of optimizing parameters as described above. In this example, since the main concern was setting up the optimization procedure with the GA, the fitness function was limited to minimizing the weight based on volume of wood used. Also, a penalty was applied to members which exceded the desired size range. That is members with thickness greater than a nominal 2 inches were allowed, but were penalized. The fitness function used by the GA returns a single value used to rank individuals. The fitness function can contain as many optimizing parameters as desired. The parameters can be weighted, and are then combined to give a single fitness value for the truss.

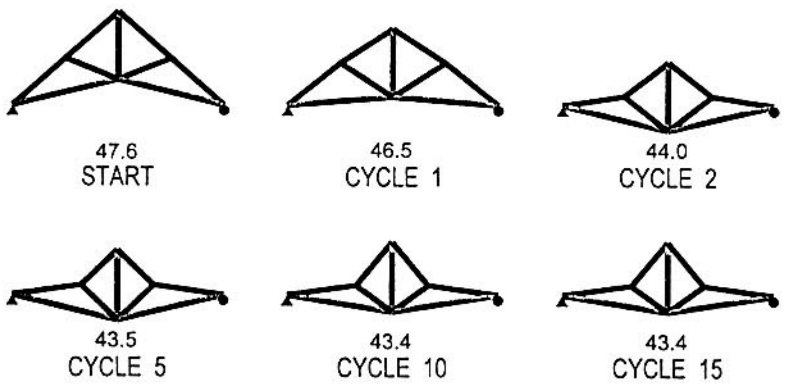


Fig. 6. Best Individual Trusses from Selected Cycles.

4. Results of Geometry Optimization

Geometries that resulted in the smallest sized members seem to have been found rather quickly. Successive generations refined these geometries to find the configuration with the shortest member lengths without allowing member forces to exceed the allowable. Although the program was run through 30 cycles, the system stabilized within the first 7 cycles. Figure 6. shows the progression of the best individuals from selected cycles. For the restrictions imposed in the example shown, the final solution was 43.4 LBS. Although there was some variation between runs, nearly the same final result was reached each time.

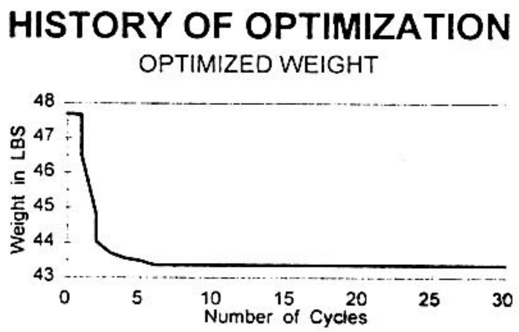


Fig. 7. History of Optimization for Weight over 30 Cycles.

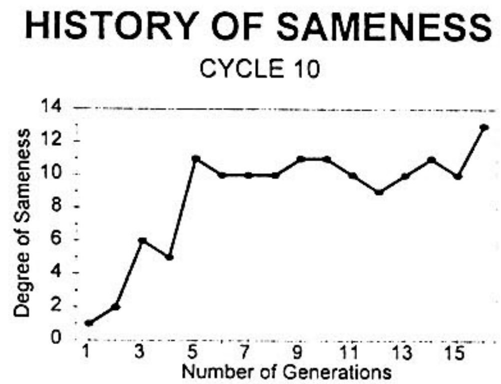


Fig. 8. Progression toward Homogeneity in one Cycle.

Figure 7. shows the history of the progress of weight optimization. Due to the randomness inherent in the GA, although the same best individual may start a cycle, the path within cycles toward the homogeneity will vary. But in each cycle a degree of stability was eventually reached. Figure 8. shows the typical progression toward homogeneity within a single cycle.

5. Procedure for Topology Optimization

The preceding example limits the possible solutions by establishing a set number of members and their incidences (how they connect). Within the defining parameters it seeks the optimal geometry. A more encompassing method would allow both the inclusion of a wider range of guiding parameters as well as the ability to actually find new forms, i.e. new topologies as opposed to new geometries based on the same topology as in the example.

Allowing the GA the ability of generating totally new topologies would give the procedure better design potential. In this way the GA could suggest totally new and unexplored topologies, rather than being limited to the given topology as in the example. To achieve this the GA must have the ability to add, subtract or rearrange members. One way to implement this ability would be to describe the incidence matrix of the finite element analysis in terms of genetic code. The incidence matrix is used to describe both the topology (how many members and how they connect) and the geometry (spatial coordinates of joints) of the system. By allowing the GA to alter the incidence matrix, new forms can be generated and considered. One way to organize a search of this type would be to develop a hierarchy of solutions. For instance a parallel could be draw with the way biological systems are ordered (at least by man) using the categories of Family, Genus and Species. For the truss example we could say: family = skeletal structures (frames and trusses); genus = trusses; species = King Post (topology). For two trusses to breed they would have to be of the same species. Individuals inside a given species would compete to produce children, and evolve toward an optimum guided by the fitness function (as in the CHC truss example above). But different species also compete for existence. They cannot interbreed, but they share the same resources and compete for survival. To program this, several species could be created and allowed to run concurrently. At some point, best individuals of the different species could be compared The poorer performers could be allowed to die out, while the better performers could be mutated into new species. Methods used for cossover in traditional GAs depend on like chromosomes being crossed. What is needed is some modified form of crossover to take place at the level of species. In this way new forms would be generated in a way that would move the solution toward better and better solutions.

6. Conclusions

A trained intuition and practical experience are usually the guidelines used in determining the appropriate shape or system for a structure. Stress calculations by FEA or other computer methods are in practice generally used as a means of verifying or sizing what is already designed. Calculations may determine sizes of members or highlight areas requiring greater attention, but they generally do not really give a designer much insight into areas not already considered. Such analytic methods only answer the specific questions put to them, they are not able to spontaneously offer new insight or solutions. This is the great advantage of Evolutionary Strategies or Genetic Algorithms. They can find totally unpredicted solutions that exceed the immediate experience of the user. The more complex the problem becomes, the greater the amount of specific experience required by the designer for a correct solution. Unfortunately, we are often left to train our intuitions on what may be far less than optimal solutions. For instance, in the simple example of the wooden truss, how would the decision be made about a specific geometry? What are the distinct qualities of a Howe, Pratt or Fink, and what are the parameters that make one more correct than the other. In the end the possibilities are too numerous and the problem remains unsolved. GAs offer a reasonable approach to solving these problems. They offer a practical tool to better train intuition.

In the simple truss example the GA was successful in finding an optimal geometry for the given parameters. With further refinement it could be built into a useful tool for structural exploration and design.

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