Effects of User Preference on Multi-Objective Roof Truss Optimization

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ABSTRACT
This paper details the incorporation of user design preference into an algorithm designed for the multi-objective optimization of large-span roof trusses. Several mechanisms are considered to embed preference into the optimization procedures of an implicit redundant representation (IRR) genetic algorithm (GA). A prediction of user preference was included in both the selection and ranking procedures of the GA. The inclusion of user preference encourages topological exploration while preserving structurally optimal designs.

Categories and Subject Descriptors
J.2 [**Computer Applications**]: Physical Sciences and Engineering -- engineering.

General Terms
Design, Human Factors.

Keywords
Roof Truss, User Preference, Multi-Objective Optimization.

1. INTRODUCTION
Previous research efforts have identified the implicit redundant representation (IRR) genetic algorithm (GA) as a useful tool for the conceptual design of large-span roof trusses [3]. The IRR GA provides flexible encoding of design variables within a set-length chromosome [5]. This flexibility allows for design alternatives to naturally evolve within a sparsely defined search space [4]. The current research effort extends the application of the IRR GA to the multi-objective optimization of large-span roof trusses by including the preferences of a human designer within the optimization criteria.

In addition to meeting structural criteria, potential truss designs must also satisfy larger considerations of practicality, economic feasibility, and conformance to the architectural program. Much of this information is readily apparent to a human designer based upon visual inspection of the design alternatives, but formulating such constraints in a manner accessible to the IRR GA is mathematically intractable. Teaching the IRR GA to recognize these "intuitive" constraints could substantially increase the suitability of design alternatives suggested for a given application.

This paper details the incorporation of user preference into the roof truss optimization algorithm developed in [3]. Section 2 discusses how and where the IRR GA accounts for user preference, while section 3 considers the effect of preference inclusion on the conceptual design process.

2. MECHANISMS FOR PREFERENCE INCORPORATION

2.1 Preference Identification
The first stages of this research effort developed a mechanism to model user design preference. The preference model results from user evaluations of 100 unique, stable truss designs evolved during the first generation of the IRR GA. These designs are grouped according to visual similarities, as quantified by nine discrete, geometrical measures of truss appearance. These measures include top chord and bottom chord flatness, number of joints, and average joint connectivity. Once analyzed for consistency, user group selections provide training information for a back-propagation neural network.

In succeeding generations of the IRR GA, the trained neural network predicts whether a user will prefer a newly generated topology. This prediction relies upon the neural network's ability to recognize preference patterns among the measures of truss appearance.

In the C++ coding, each individual in the IRR GA pools is described by several class attributes, one of which is the "preferred" attribute. This attribute records predictions made by the neural network. The algorithm assigns a preferred value of "1" if the network predicts that the user will like a new design and a value of "2" if the user will not.

2.2 Description of the Algorithm
The IRR GA implementation used in this research was developed in [3]. To optimize designs from a structural standpoint, the algorithm seeks to minimize truss weight and

mid-span deflection while accounting for kinematic stability, constructability limits on length, and allowable member stresses. Relevant details about the algorithm will be summarized here.

Maintaining population diversity proved to be a difficult challenge. As the major goal of this research is to provide engineers with a wide range of equally viable design alternatives, several techniques were implemented to help promote this objective.

Based on the Strength Pareto Evolutionary Algorithm described in [1], Paik [3] saved top-ranked individuals in external pools. These pools ensured that previously discovered Pareto solutions remained in all generations. A second set of external pools recorded all stable, unique topologies discovered by the IRR GA, regardless of performance.

Also based upon the Strength Pareto Evolutionary Algorithm, the strength of each individual, in terms of the number of solutions it dominated, was calculated. This strength was combined with a fitness-sharing measure, as outlined in [2], and a composite measure of constraint violations to create a "total fitness" measure. The total fitness measure served as a tie-breaker during the selection process.

In the current formulation, all constraints are treated as separate objectives. One function, dominate(), is used to compare solution-pairs based upon weight, deflection, and the degree of constraint violation. This function serves to determine solution dominance in both the ranking and tournament selection procedures.

When a clearly dominant solution does not emerge from this comparison, alternate fitness measures are used. During ranking, this measure is a composite fitness function. Tournament selection relies upon a total fitness value to break dominance ties, as mentioned above. In addition to forming a strength calculation for use in the total fitness measure, ranking also serves to identify Pareto optimal solutions and sort the external pools so that low-ranking solutions are replaced with more highly performing individuals.

2.3 Preference Locations and Trials

Based upon the fitness assessment procedures described in the previous section, the following three locations were identified for potential inclusion of user preference:

1) The dominate() function, which compares objective values for two individuals.

2) The composite fitness function, which provides additional information during ranking.

3) The composite penalty function, which forms part of the total fitness measurement to provide additional information during tournament selection.

Five different mechanisms explored the effect of user preference on the IRR GA by placing the preferred attribute into one or more of the above locations. A series of trials, with base geometries varying in either span length or parametric choices, incorporated each mechanism. User preferences remained constant throughout all simulations. This consistency was accomplished by saving a file of potential designs during an initial run and reusing it during the preference input process, rather than asking the user to evaluate new designs for each trial.

The mechanisms were compared based upon their ability to successfully promote user preferences without degrading the structural performance of ranking individuals. This comparison accounted for whether the average value of the preferred attribute among top ranking individuals decreased over time. The number of final-generation topologies suggested by the IRR GA created a method for evaluating whether a mechanism enhanced the conceptual design process. Similarities were also drawn between the final-generation topologies and user selections to indicate how well each mechanism guided the IRR GA to more desirable design alternatives. Lastly, plots of weight vs. deflection illustrated the first-rank Pareto front solutions and provided information about structural behavior.

After considering the above criteria, the most effective formulation proved to be one that included preference in both the dominate() function and in the composite penalty function. This mechanism optimized the preferred attribute and reflected user preferences. Pareto fronts for all mechanisms illustrated that preference incorporation did not reduce the structural performance of top-ranked individuals and created more diverse design populations. These effects are discussed more fully in the next section.

3. EFFECT OF PREFERENCE INCORPORATION

The overall effect of including a user's design preferences in the IRR GA optimization process was to increase exploration within the feasible region. This exploration manifested itself in both the number and diversity of final-generation topologies suggested by the GA as well as in the creation of substantially fuller Pareto fronts. Figures 1 through 3 illustrate the qualitative effects of user preference on the Pareto fronts discovered by the IRR GA.

In Figure 1, the Pareto front consists of multiple curves. Regions of dense exploration give rise to several solutions, but gaps appear in the overall curve. These gaps indicate regions of the tradeoff curve not represented by the population of solutions obtained by the IRR GA. Since the solutions lying along the Pareto front directly correlate to the number of design alternatives presented to the user, a more complete Pareto front is clearly desirable for conceptual design.

When truss designs are optimized according to both structural and preference criteria, the final generation Pareto fronts resemble those shown in Figures 2 and 3. In Figure 2, the user's preferences coincided with the structurally optimal designs independently discovered by the IRR GA. Therefore, the user's input does not substantially change the appearance of the suggested alternatives. Instead, the user's preferences lead to a more fully explored Pareto front. The disconnected regions meet to form a more continuous curve.

Although the Pareto fronts are remarkably similar in Figures 1 and 2, it should be noted that the design topologies lying along these fronts may not match up exactly. Typically, simulations that accounted for user preference generated a larger number of unique topologies than simulations that considered only structural criteria. Therefore, although design alternative *forms* may not vary when user preference and structural criteria are in agreement, the *number* of design alternatives usually increases and thus enhances the conceptual design process.

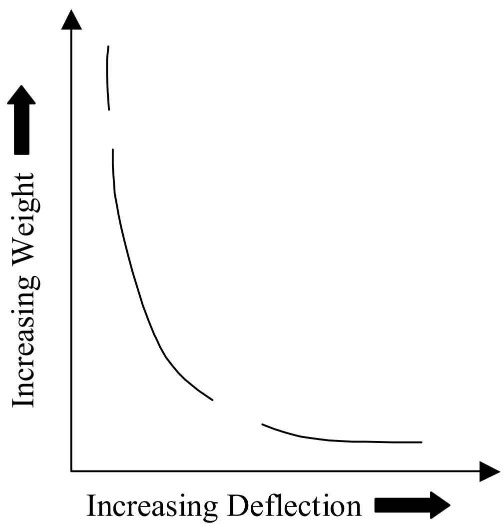

Figure 1. Example Pareto front obtained using only structural optimization criteria.

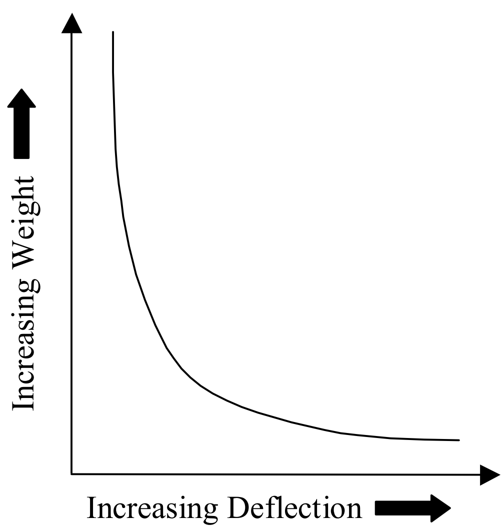

Figure 2. Example Pareto front obtained using structural and preference criteria. Design preferences align with those existing already in the structural optima.

The "conventional" structural designs proposed by the IRR GA, however, may not agree with the architectural program for a given truss system. A user may indicate a preference for more unusual truss designs to achieve a topologically unique form. In that instance, two Pareto "fronts" may emerge among top-ranked solutions, as shown in Figure 3.

The two curves shown in Figure 3 are contained within a single Pareto front for this population. The dual-curve effect occurs because the front is plotted in only two-dimensions, illustrating values for the weight and deflection objectives only. The third objective, user preference, is plotted indirectly and manifests itself by creating a second curve.

The first curve of Figure 3 represents the expected tradeoff curve. The solutions lying along this curve closely resemble those discovered in the scenarios represented by Figures 1 and 2. These solutions are the most strongly performing from a structural perspective. However, the user has indicated a preference for unusual truss designs, and the truss alternatives along the left-most curve of Figure 3 are unlikely to satisfy this criterion.

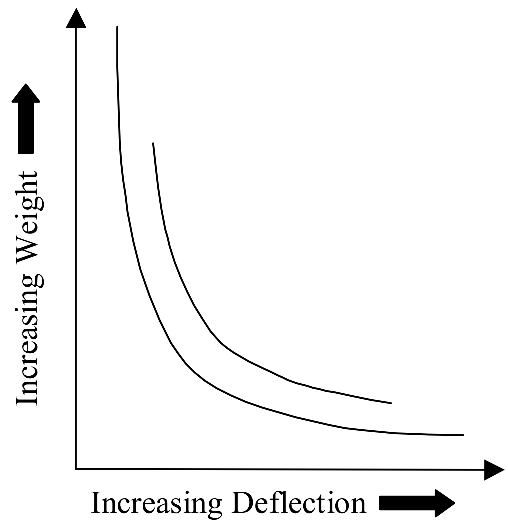

Figure 3. Example Pareto front(s) obtained using structural and preference criteria. Design preferences diverge with those that exist in the structural optima.

The second curve illustrated in Figure 3 forms in an effort to better reflect the user's preferences. Since "conventional" truss designs are inadequate, the IRR GA must generate new forms to address this need. These new designs may sacrifice structural performance to better satisfy user preference. Over time, this second "front" will draw closer to the first, and often the two fronts become integrated. The most structurally optimal of the new designs will remain in the united front.

As the proceeding figures illustrate, incorporating user preferences into the IRR GA significantly increased exploration. This result may be better comprehended by considering the architecture developed in [3]. The IRR GA is extremely useful in undefined search spaces because of the flexibility with which it encodes design variables. However, this flexibility proved to be a deficit in a multi-criteria environment with a small feasible region [3]. Preserving unique truss topologies and encouraging the discovery of more led to a sub-process architecture to separately analyze each group of similar designs [3]. These multiple processes corresponded to high computation costs and a slow run time.

When the feasibility region was further narrowed by addition of the preference criterion, fewer sub-processes were required, thus reducing the computational effort to complete the simulations. Contrary to expectations, narrowing the feasible region had a beneficial effect on exploration. Instead of investing resources to "fine-tune" undesirable topologies, the smaller number of sub-processes focused on designs interesting to the user and provided locations for new truss forms to develop.

4. CONCLUSIONS

This work describes the effects of user preference on the multi-objective optimization of large span roof trusses. The optimization process was accomplished using an implicit redundant representation genetic algorithm. A prediction of user preference was included in both the selection and ranking procedures of the GA.

Overall, preference implementation enabled the IRR GA to identify designs more likely to be acceptable to the user while simultaneously improving the algorithm's ability to discover additional design alternatives. Pareto fronts from analyses with and without user preferences reveal that this improved exploration did not detract from the optimization of the structural criteria. In instances where user preferences aligned with structural optima, the IRR GA still received the benefit of added exploration. When user preferences promoted non-optimal designs, the IRR GA strove to incorporate these preferences while retaining the most structurally efficient individuals.

The ability to reflect user preference is of primary importance for the IRR GA, or any other automated optimization algorithm, to successfully aid in conceptual design. By incorporating the human designer into the optimization process, it is possible to generate large span roofing systems that satisfy structural criteria and meet demands specific to individual design domains.

5. ACKNOWLEDGEMENTS

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