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Conceptual frame design by heuristicly refined multiobjective random search

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Abstract

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The use of mathematical optimisation methods in the engineering design process has traditionally been restricted to the detailed design stage. Using the design of a frame structure as a case study, this paper explores the potential of a heuristicly refined multiobjective random search approach to conceptual design stage. The key elements of this approach are 1) a random search based optimisation method (to simulate creativity), 2) designer-specified heuristics (some grammatical rules to allow different frame configurations to be explored), and 3) a multiobjective optimisation approach (to identify competing concepts occupying different parts of the trade-off surface). The results presented demonstrate the success of this approach in exploring a multiplicity of different design configurations and presenting the designer with a variety of *Pareto*-optimal concepts worthy of further consideration.

Key words : generative grammars, multiobjective optimisation, topology optimisation, conceptual design

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บทคัดย่อ

อภิชาติ ศุภพิชญ์นาม

การออกแบบเชิงความคิดของโครงสร้างเฟรมด้วยเทคนิคฮิวริสติกลี่รีฟายน์มัลติอ๊อบเจคทีฟออปติไมเซชั่น

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โดยทั่วไปแล้ว การประยุกต์ใช้เทคนิคออปติไมเซชั่นแบบต่าง ๆ ในงานทางวิศวกรรมนั้น ค่อนข้างจำกัดอยู่ในช่วงหลังของกระบวนการออกแบบ (detailed design stage) บทความนี้ได้กล่าวถึงการศึกษาถึงศักยภาพของเทคนิคออปติไมเซชั่นวิธีหนึ่งสำหรับการออกแบบเชิงความคิดในช่วงแรก (conceptual design stage) ซึ่งได้ผนวกเอาการสร้างสรรค์รูปแบบที่หลากหลายและเหมาะสม (heuristicly refined generation) ด้วยกรณีศึกษาของการออปติไมเซชั่นโครงสร้างเฟรมเชิงความคิด (conceptual frame design optimisation) เทคนิคที่นำเสนอดังกล่าวประกอบด้วยส่วนสำคัญ 3 ส่วนคือ 1) การใช้ออปติไมเซชั่นแบบสุ่ม (random search) ซึ่งเสมือนเป็นการเลียนแบบการสร้างสรรค์ความคิดของมนุษย์ 2) การสร้างสรรค์รูปแบบและโครงสร้างที่เหมาะสมตามกรอบของนักออกแบบ (designer-specified heuristics) ซึ่งถือเป็นกฎที่กำหนดการสร้างหรือประดิษฐ์รูปแบบของชิ้นงาน ในลักษณะเดียวกับไวยากรณ์ในการสร้างคำ วลี และประโยค จนเป็นภาษาต่าง ๆ และ 3) เทคนิคมัลติอ๊อบเจคทีฟออปติไมเซชั่น ซึ่งช่วยทำให้สามารถเปรียบเทียบรูปแบบต่าง ๆ ของชิ้นงานได้ว่ามีจุดเด่นจุดด้อยในด้านใดจากพื้นผิวเทรดออฟ (trade-off surface) ผลจากกรณีศึกษากับโครงสร้างเฟรมดังกล่าว แสดงให้เห็นว่าเทคนิคที่นำเสนอนี้สามารถสร้างสรรค์โครงสร้างเฟรมรูปแบบต่าง ๆ ได้ พร้อมข้อดี ข้อด้อย และข้อเสนอแนะที่เป็นประโยชน์สำหรับนักออกแบบเพื่อการพิจารณาในรายละเอียดในขั้นตอนต่อไป

ศูนย์เทคโนโลยีโลหะและวัสดุแห่งชาติ สำนักงานพัฒนาวิทยาศาสตร์และเทคโนโลยีแห่งชาติ 114 อุทยานวิทยาศาสตร์ประเทศไทย ถนนพหลโยธิน อำเภอคลองหลวง จังหวัดปทุมธานี 12120

Conceptual design is the creation of functions to fulfil customers' needs and the creation of form and behaviour to realize those functions (Benami and Jin, 2002). During this design stage, designers have the freedom to generate and explore many possible designs without being constrained by parameters that are normally encountered at later design stages. Design at the conceptual stage is crucial and whether a good or bad design is attained depends very much on this early stage of the design process. Traditionally, ideas and conceptual designs are generated through brainstorming where ample time and good collaboration are necessary for the production of such creativity. Research in cognitive science, computer science, and design methodology has been attempted to provide a foundation for development of many intuitive techniques that stimulate human creativity and, recently, the use of optimisation methods is one alternative for such task.

Optimisation has been used in the evolutionary design for years. However, most practical optimisation approaches usually start with an existing design and attempt to vary those parametric parts of the design that need improvement. In other words, the use of mathematical optimisation methods in the engineering design process has traditionally been restricted to the detailed design stage. While better (detailed) designs are obtained, innovation and creativity are suppressed, because the designer is, by this stage, working with a fixed chosen concept. The use of optimisation, normally in a form of a computational tool, has been considered inappropriate in the earlier conceptual design stage, because it is claimed that the computer, unlike the human designer, is not in itself creative.

In recent years this viewpoint come under strong challenge. It has been demonstrated that evolutionary search algorithms running on computers can be used to evolve designs in a seemingly limitless number of application domains (Bentley, 1999). According to Boden (1992), creativity is only possible by going beyond the bounds of a representation, so it is obvious that optimisation framework for conceptual design must be capable of design generation beyond the predefined representation. The successive application of simple design modification rules defined by a so-called *generative grammar* enables complex design spaces to be explored beyond the initial representation efficiently (Stiny and March, 1981). Generative grammars, when coupled with a stochastic optimisation algorithm, most commonly the Simulated Annealing (SA) algorithm (Kirkpatrick *et al*., 1983), form a design exploration methodology known as *shape annealing* (Cagan and Mitchell, 1993). Recently (Suppapitnarm *et al.,* 2004) has investigated the potential benefits of coupling a generative grammar for the design of bicycle frames to a multiobjective SA variant. This paper explores these ideas further and illustrates the potential benefits of the approach to conceptual frame design.

1. Framework of the approach

There are three key elements in attempting to generate conceptual design of frame structures. These are a stochastic optimisation method, designer-specified heuristic rules for structural frame design and a multiobjective optimisation approach.

1.1 A stochastic (random) optimisation method

The strong stochastic element to the search and exploration procedure is intended to simulate the inventiveness of initial conceptual brainstorming of the design process and to ensure that the conceptual design space is widely explored. In this study Simulated Annealing (SA) (Kirkpatrick *et al*., 1983) was used to accomplish the task. Simulated Annealing is a search technique that, by its nature, is quite suitable for conceptual design exploration in many ways. Besides its strong stochastic characteristics that simulate the inventiveness of concept generation, SA can handle design problems with several requirements - a common situation often found during conceptual design stage, with simple implementation. Compared with other search and exploration methods with strong stochastic elements, such as Genetic Algorithms (Goldberg, 1989) or Evolution Strategies (Schwefel, 1995), the performance of SA algorithm is less sensitive to the design representation and control parameters. SA smartly moves from only the accepted designs that have potential to be good designs or to lead to good designs. Whether the designs it generates are accepted depends on a rule that follows the arbitrary cooling (annealing) state of solids. For single objective optimisation, the implementation seeks to minimise a given objective, f, by applying small random changes to the control variables of a design and considering the change in value of the objective, Δf. For a decrease in the objective (a better design), the resulting change in solution is accepted and further search is continued from this point. However, if the resulting change causes an increase in the objective (a poorer design), the new solution is accepted with probability $\exp(-\Delta f/T)$; T is a control parameter referred to as the *temperature* of the system. For large temperatures, virtually all new designs are accepted irrespective of the sign of Δf. Conversely, for small temperatures, only small positive excursions in Δf are accepted, if at all. Temperature, therefore, represents the level of *disorder* in the search process. Thus, the search is initiated under a high temperature to allow for as much exploration of the design space as possible and, as the temperature is then decreased to zero in some regulated fashion, the search, hopefully, converges onto a globally optimal solution. An implication of this feature is that accepted designs are not always better designs in SA. By allowing the search to, sometimes, progress from poorer designs, it can potentially move away from locally optimal solutions.

1.2 Designer-specified heuristic rules for structural frame design

A generative grammar is incorporated to help achieve the goal of exploring different design configurations - a key requirement in the conceptual design stage of the design process. Generative grammars specify a set of designs by the transformations required to generate that set (Gips and Stiny, 1980). In the context of design, the interest in specifying a set of alternative designs derives from the fact that the set can then be searched for optimal designs. *A shape grammar* defines the allowable transformations of shape, either with fixed or parametric dimensions, which can be used to generate a language of spatial design (Stiny, 1980). The language of structural design defined by the grammar can be used to generate both known designs, from which the grammar was originally derived, and new, and often innovative, designs that still conform to the grammar used to generate them.

There are two types of grammar. Simple generative grammars require little information to formulate them, but the designs they generate require further validation, normally through some form of test mechanism. On the other hand, knowledge-based grammars, as their name implies, contain more application-specific knowledge, and the designs they generate are therefore inherently feasible. Since SA is a generate-and-test mechanism, functional knowledge is placed in the optimisation model. The purpose of the incorporated grammar is then to define an intended design that will be further validated through evaluation within the optimisation process. Placing functional knowledge in the test mechanism is attractive because it allows *unbiased* exploration of topologies, which could lead to the generation of innovative designs. In addition, a simple generative grammar can be applied to a wider scope of design problems making it suitable for conceptual design exploration.

A simple grammar for rigid frame structures has been implemented and applied to various conceptual bicycle frame design problems (Suppapitnarm *et al*., 2004). The grammar consists of *shape* and *size modification* rules, similar to those in the truss grammar developed by (Shea and Cagan, 1999), and four *topology modification* rules. The shape modification rule moves the position of a node a small random amount. The size modification rule makes a small change to the size of the cross-section of a member (for instance, if the member is of circular, tubular section, a small change is made to its radius and/or thickness). The topology modification rules modify the topology of frame designs by adding or removing a member, a node or a combination of two so that a new design topology is generated.

1.3 A multiobjective optimisation approach

Straightforward optimisation that focuses on the maximisation or minimisation of a single objective will almost inevitably converge on just one part of the search space. In contrast, multiobjective optimisation that focuses on exposing the *trade-off surface* between competing objectives usually leads to the identification of a multiplicity of equally good (from a multiobjective perspective) designs (*Pareto*-optimal solutions) where the advantages, disadvantages and compromises associated with each of the concepts are highlighted.

In keeping with the choice of SA explained earlier, Multiobjective Simulated Annealing (MOSA) (Suppapitnarm *et al*., 2000) was employed in this study. The MOSA method searches for a set of non-dominated solutions, i.e. solutions for which no other solution is better with respect to all requirements, and provides the designer with information about the various trade-offs between the design objectives. MOSA does this by iteratively comparing the quality (objectives) of each new design with that of all the designs in the established archive (the record of all non-dominated solutions found). If the new design dominates any existing designs in the archive (i.e. has equally good or better values for every objective and at least one objective is better), those designs are removed and the new design is added. If any designs of the archive dominate the new design, it is not archived. If the new design neither dominates nor is dominated by any design, it is added to the archive. It is this set of archived (non-dominated) solutions that eventually forms the trade-off surface between each of the competing objectives. The principle of archiving in MOSA is

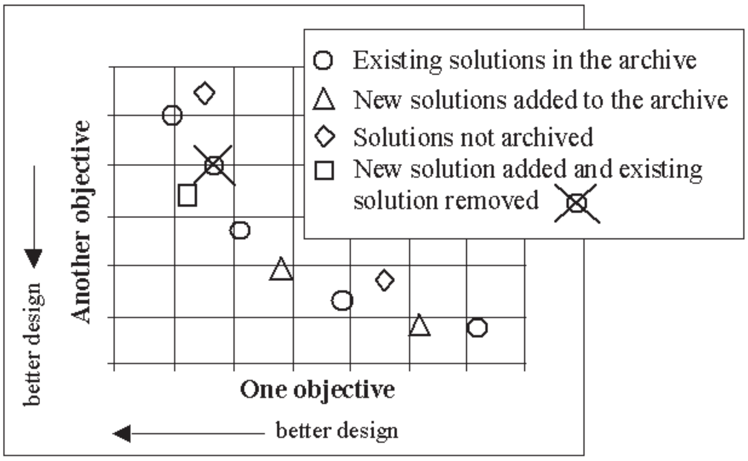

Figure 1. Archive evolution (Suppapitnarm *et al.*, 2000).

illustrated in Figure 1, for a two-objective problem. MOSA keeps record of all good designs and returns to them periodically during search. At each return, the selection of such design favours the most isolated and extreme solutions amongst those in the archive, in order to try to ensure a uniformly distributed exposure of solutions on the trade-off surface. More implementation details of the MOSA algorithm are given in (Suppapitnarm *et al.*, 2000). In this regard, MOSA makes use of prior knowledge for the search to continue. Other search techniques also make use of past knowledge to guide the search but in different ways. For example, gradient-based techniques such as Quasi-Newton or simplex method accumulate knowledge in terms of the past few function evaluations and their derivatives to direct the search. Most evolutionary algorithms and stochastic methods, however, maintain a database of potential solutions, normally known as a *population*, and keep improving such a database record as the search continues. They simply train themselves through a statistic record of generated solutions without constraining the search direction using the established knowledge as in gradient-based techniques. It is obvious that, because of this, search exploration with stochastic methods is likely to be wider - a desirable circumstance that is required particularly for conceptual design development.

1.4 Framework structure

Figure 2 presents a flow chart of the optimisation process with the frame grammar introduced at the design generation phase. The process can be summarised as follows;

1. When a new design has been generated using the grammar rules, its structural performance is analysed (objectives and constraints are evaluated).
2. This design is then compared with solutions already in the archive.
3. If the new design is archived (possibly replacing existing archive solutions in the process), then it is definitely accepted.
4. If it is not archived, then it is accepted with a probability that follows the annealing state.
5. As in conventional SA, the temperatures are periodically lowered.
6. In order to try to ensure that the *Pareto*-optimal surface is fully explored, the search is periodically restarted from a solution chosen from the archive (a return to base is made).

Note that during the new design generation with the frame grammar, shape and size modification rules are mostly applied until a better design (or an equally good design, in a multiobjective context) cannot be found for a predefined number of iterations. This ensures that promising design topologies will be sufficiently

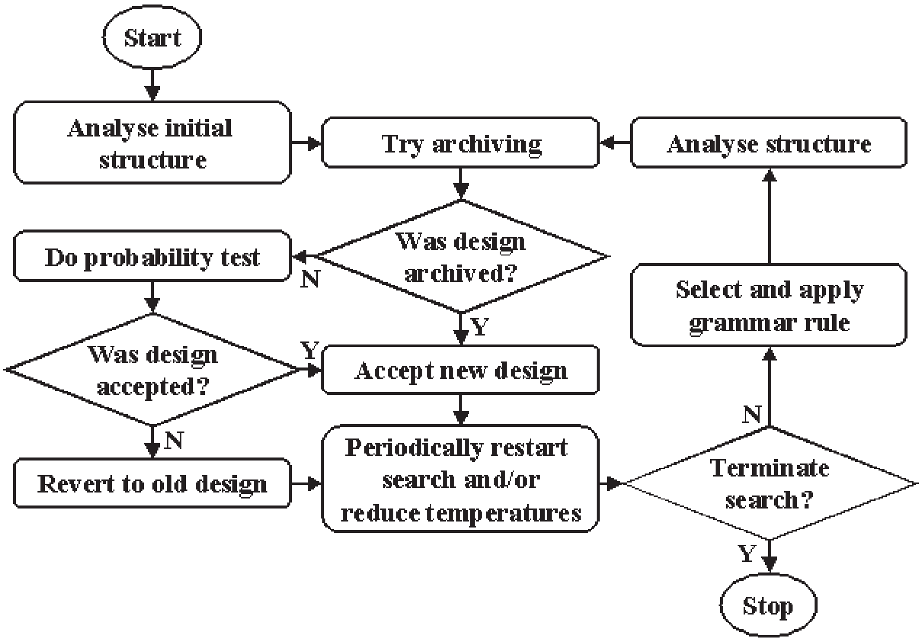

Figure 2. Flow chart of the optimisation process with frame grammar (Suppapitnarm *et al.*, 2004).

explored, while a bad topology (one for which feasible designs cannot readily be found) will be rejected quite quickly.

2. Generation of conceptual frame designs

The proposed method is now attempted on the traditional 10-bar truss problem, similar to that presented by Bennage and Dhingra (1995), except that the design is now converted into a frame structure and the design space is not restricted to 10 elements. Different frame topologies can be generated and considered simultaneously within the design space by the proposed framework (a conceptual design exploration within the frame structure). The modified representation of the structure is shown in Figure 3. The structural members are made of aluminium with Young's modulus, E = 68.95 GPa and density, ρ = 2768 kg·m^{-3}. The structure is required to support two loading points, each carrying 445 kN, with two fixed (not pin) supports on the wall. The allowable stress, σ_a for all members is limited to 172 MPa and the allowable displacement in each of the x and y directions is also limited to 50 mm. The only variables in the problem are the cross-sectional areas, A_i, of the members of the frame where their limits are: 64.5 mm^{-2} $\leq A_i \leq$ 216 cm^{-2}. Note that because of varying topologies, the number of design variables changes automatically according to the number of tube members of the frame.

With emphasis on structural and aesthetic design goal in mind for this conceptual frame design, three objectives were established for the problem:

1. Minimisation of structural mass;
2. Minimisation of the average deflection of all free nodes (i.e. to maximise the stiffness of structure);
3. Minimisation of variation in member length (δ_L). The aesthetic models used in structural design are commonly derived from concepts such as uniformity, proportion, contour and symmetry (Leonhardt, 1982). It is assumed that, for this problem, a frame design with uniform tube length will look aesthetically pleasing in its own simplicity.

The search started with a minimal number of tube members joining 4 points of the frame

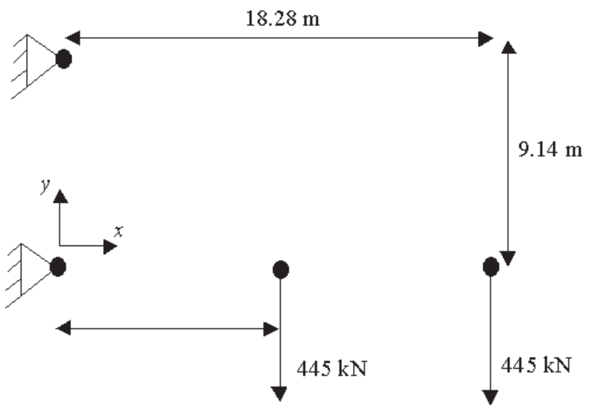

Figure 3. Problem representation and design space.

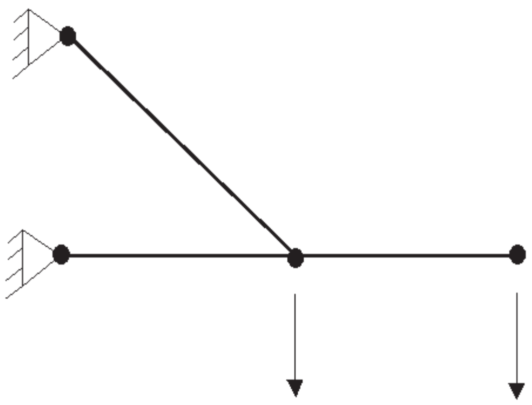

Figure 4. Starting design.

structure as shown in Figure 4. Note that rotation is not allowed in all nodes so a triangulation constraint (for a pin-jointed truss) was relaxed and hence, the starting design could be a stable structure as long as the stresses and deflections of the design are within the allowable limits. This is another advantage of the method. It does not require much information to initialise the design and the starting design is not necessarily feasible. However, the design with a minimum number of connections is likely to violate the structural constraints, and, if that is the case, the design will automatically be transformed to move away from the initial structure during search.

Figure 5 shows the evolution of the trade-off surface obtained after 20000, 50000 and 100000 iterations of one test run with the optimisation framework applied for this conceptual frame design. It is clear that a better, more uniform trade-off surface was established as the time is left running longer. Note that, because it is the three objective problem, the trade-off surface does not appear as a single line as illustrated earlier in Figure 1. It is interesting to see that the strength of the trade-off between the aesthetic measure and the other objectives are similar to that of the trade-off between the mass and deflection (which, for structural design, is normally a strong compromise). This suggests that, based on the current optimisation model, there is also a compromise on structural performance for aesthetics.

Among the 348 optimal designs identified after 100000 iterations, 16 different frame topologies were explored and are as shown in Figure 6. None of these optimal designs has an exact 10-bar topology, although many designs having this topology had been generated during search, see Figure 7. However, considering a design in Figure 7(e) with that in Figure 6(b), it is clear that many designs with a 10-bar topology were gradually transformed towards the optimal designs. Therefore, for this problem, it is not surprising why such a topology is not identified as optimal. It can also be seen from Figure 8, where a direct comparison of the trade-off between the mass and deflection objectives is performed between the fixed 10-bar structure optimisation (Suppapitnarm *et al.*, 2000) and the present conceptual frame design (with varying topology), that the 10-bar topology has, overall, an inferior quality according to these two objectives alone. Note that the trade-off surface established during the 100000 iteration search may not yet represent the final trade-off surface of the variable topology, and, it is anticipated that if the search is left running longer, better frame designs will be explored. Since the proposed approach is not intended to find the true global optimal designs but rather to establish the trend of the trade-off surface and to discover possible optimal conceptual designs, the 100000 iterations search is considered sufficient for the intended study of the problem.

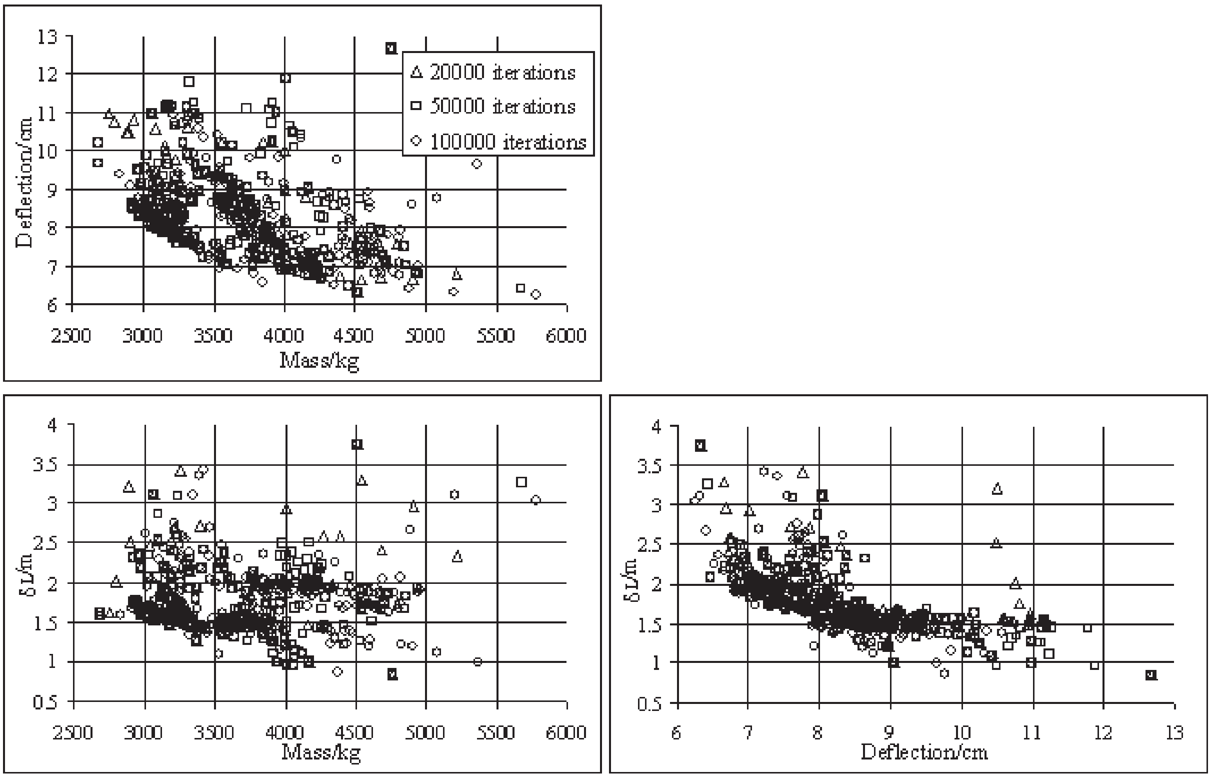

Figure 5. Evolution of trade-off surface in two-objective projection of the three objectives after 20,000, 50,000 and 100,000 iterations for conceptual frame design generation.

The most common of the optimal designs have topology (f), the topology that favours the light-weight consideration as seen from Figure 9 (refer to Figure 6 for layout of each topology in bracket). Note that, for clarity and ease of discussion, not all the optimal topologies are shown in Figure 9. If stiffness is the concern, three topologies, (d), (e) and (l) tend to highlight desirable feature in this objective performance. Regarding aesthetics, designs having topology (g) are identified as the most beautiful designs although their structural performances in the other two objectives are not that desirable. Many designs with topologies (h) and (m), however, highlight attractive aesthetic measures without too much compromise in structural performances as opposed to designs with topology (g).

It is clear that different design topologies can have different emphases on objective performances. With the multiobjective trade-off study combined with designer-specified heuristic rules for different design generation, the relationship between design configurations (forms) and the required performances (functions) can be identified. This feature of the approach helps fulfilling the conceptual design goal as it provides a good source of knowledge to the designer so that he can make an informed decision on the chosen design configuration before focussing on its details during the later design stages.

Conclusions

An optimisation approach to conceptual design based on a combination of grammatical transformation (designer-specified heuristics) and stochastic, multiobjective search has been presented and illustrated using the case study of conceptual

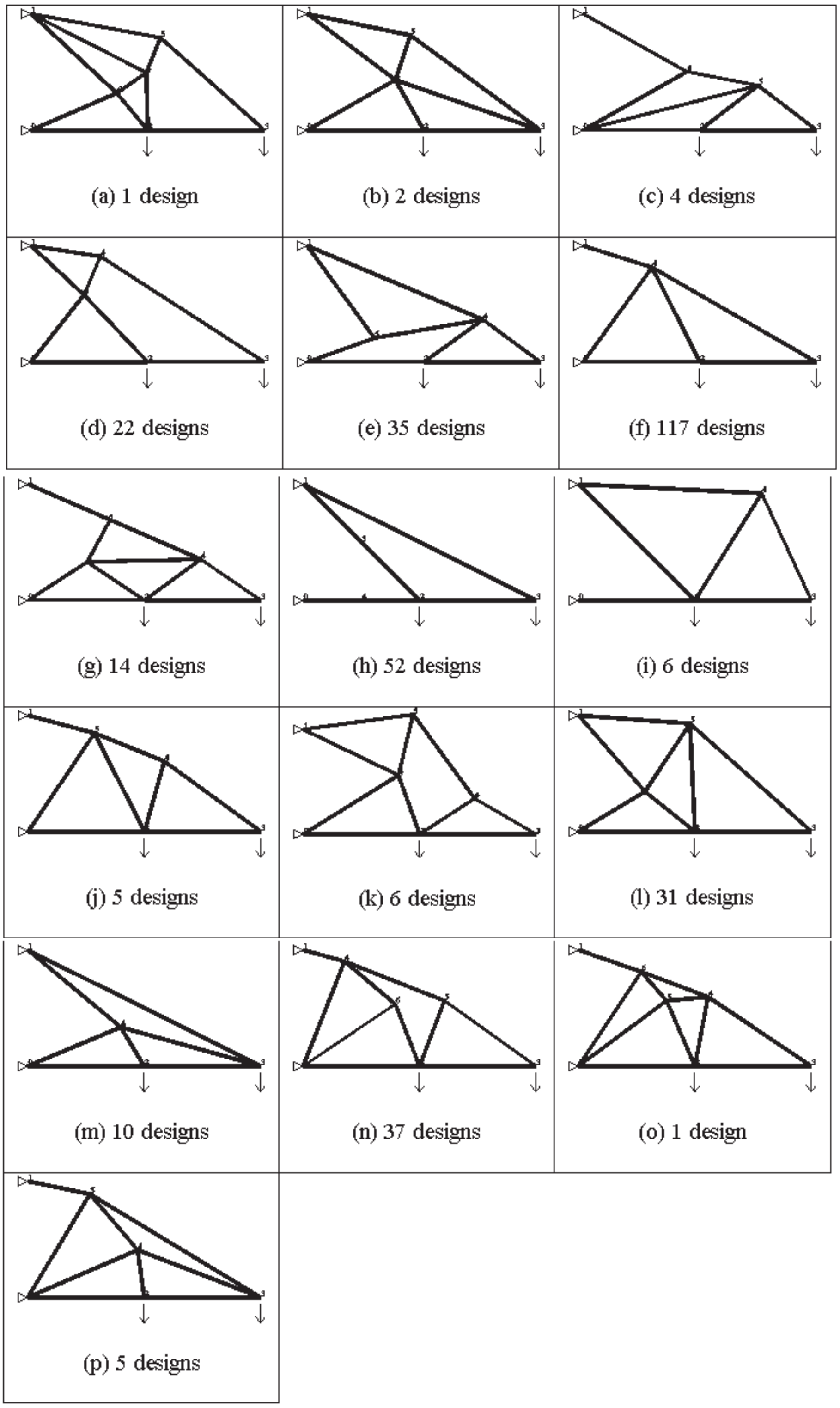

Figure 6. Optimal topologies of the conceptual frame design problem (each with a number of designs found in the trade-off surface) identified after 100000 iterations.

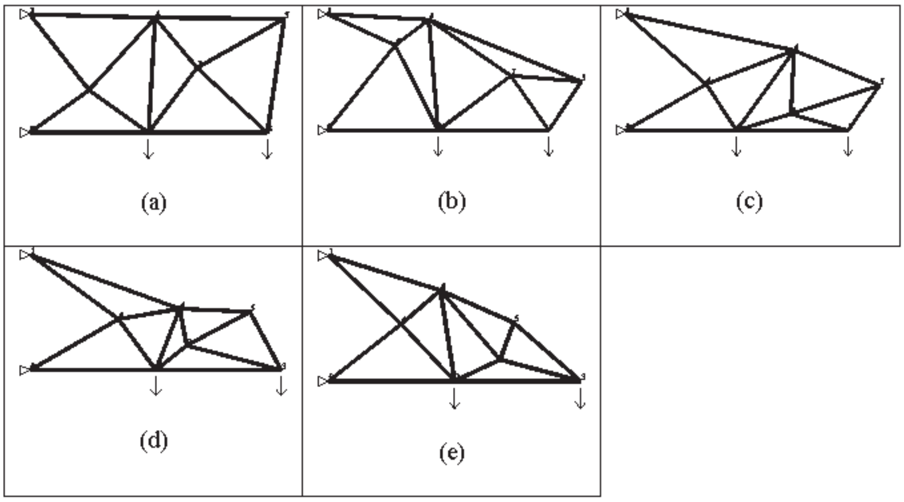

Figure 7. Generated designs with 10-bar topology.

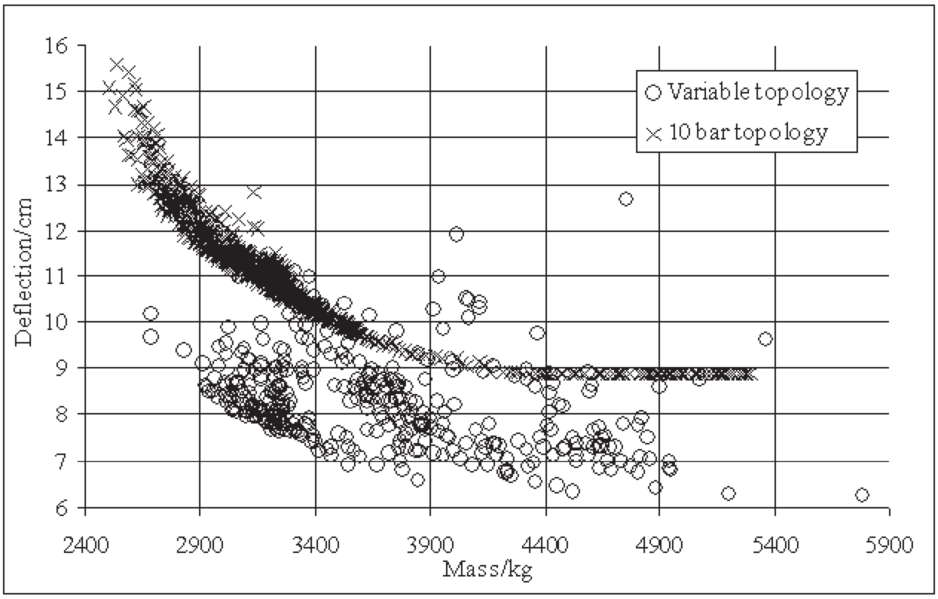

Figure 8. Comparison of the trade-off surface between variable topology and the 10-bar topology (Suppapitnarm *et al.*, 2000).

frame design. The simultaneous use of topological, shape and sizing optimisation allows practical design considerations to be incorporated into the search process, while the stochastic, multiobjective search facilitates a thorough exploration of the conceptual design space.

The results presented demonstrate that the approach is capable of generating (from a minimally simple initial design) and then optimising a wide variety of different design concepts. The trade-off surface obtained illustrates, for the benefit of the designer, the relationships between different concepts and performance matrices, as different design topologies tend to cluster on and highlight particular parts of the trade-off surface. The insight this gives can only enhance the designer's under-

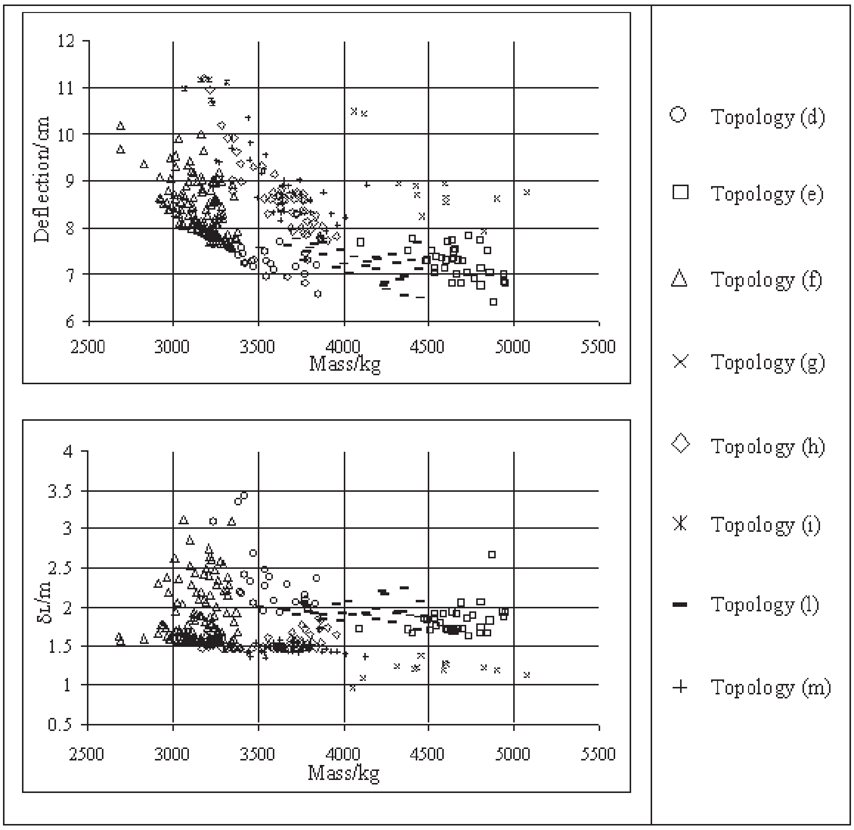

Figure 9. Trade-off surface after 100000 iterations by design topologies.

standing of the nature of the design space pertaining to the problem at hand. A wide variety of different concepts are explored and their advantages and disadvantages revealed to assist the designer in choosing concepts worthy of further, more detailed investigation.

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