Guided genetic algorithm for dome optimization against instability with discrete variables

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ABSTRACT

Stability is a decisive factor in the design of domes. The relative gradient of joint well-formedness (gra_r) is defined in the present paper to represent the stability of domes from the perspective of joint well-formedness. The lowest value of gra_r (gra_r_{min}) functions as an indicator of the buckling capacity. The gra_r and gra_r_{min}, numerical representations of dome stability, lay the mathematical groundwork for optimization against instability. Characterized by clarity in physical meaning and simplicity of calculation, gra_r is suitable for a high-performance optimum algorithm. To improve the buckling capacity of space domes, an optimization model against instability, which takes the maximization of gra_r_{min} as the objective and the member sections as discrete variables, is formulated subject to the constraints on design specifications and steel consumption. Subsequently, a guided genetic algorithm (GGA) is proposed for the stability optimization of large-scale space domes. Information on joint well-formedness that is calculated for a fitness function is re-used to identify stability-vulnerable elements and stiffness-redundant members. Mutation then operates on these members under the guidance of an instability mechanism. The GGA works on guided mutation rather than stochastic mutation of the canonical genetic algorithm, to realize oriented evolution for rapid search. The performance of the proposed method is validated on two large-scale domes. For real-life space domes, the GGA presented shows advantages in computational efficiency, robustness and engineering application, particularly for real-life large-scale domes.

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1. Introduction

Stability plays a dominant role in the design of space domes. In 1979, Riks [1] proposed the arc-length method, which overcame the divergence problem in the vicinity of limit points. Traced by the nonlinear arc-length method, dome stability is represented by an accurate critical load denoted as P_{cr}. To improve the serviceability of the dome, Tugrul [2] and Talaslioglu [3] took P_{cr} as an index of stability and conducted multi-objective (including stability) optimization. It is time consuming to take P_{cr} as a representation of dome stability because P_{cr} requires nonlinear iterations. Departing from the numerical method, Kamat et al. [4] and Plaut et al. [5] described dome stability from the viewpoint of energy. Subsequent optimization aimed at enhancing the stability was performed on a two-bar planar truss and a four-bar space truss based on the principle of stationary total potential energy. However, this analytical approach is confined to simple trusses and fails to optimize real-size domes with a large number of joints and beam elements.

In contrast to the analytical method, heuristic algorithms are applied to various optimizations of real-life structures [6]. Among all the heuristic algorithms, the genetic algorithm (GA) enjoys the most popularity [7]. In 1986, Goldberg and Samtani [8] first applied a GA in the optimization of a planar truss. Contemporaneously, Rajeev and Krishnamoorthy [9] and Hajela and Lin [10] developed a GA for discrete size optimization. With the extensive application of GAs in structural optimization, the complexity of the optimization model increased, resulting in an upsurge in computing time. One solution to lessen the computing time is to take advantage of high performance computing technologies, such as parallel processing [11–13] and distributed computing [14]. Sarma and Adeli [15] developed a bilevel parallel GA, that makes use of simultaneous parallel processing and distributed computing. Another approach, which is more applicable and straightforward, is to develop highly-efficient optimization techniques. Surrogates or meta-models are introduced in evolutionary algorithms for approximating the fitness function [16,17]. Vincenzi and Savoia [18] coupled response surface (the surrogate model) and differential evolution for parameter identification problems. To reduce the number of variables, Toğan and Daloğlu [19,20] proposed an adaptive member grouping strategy. However, a GA with this strategy may lead to a near-optimal rather than optimal result. To overcome this disadvantage, Kociecki and Adeli [21,22] further developed a two-phase GA by considering both the efficiency of computing and the efficiency of optimization. In the first phase, the GA is implemented on the structure divided into a few regions preselected by the designer until a near-optimal solution is found. Then, in the second phase, the GA is applied

to the expanded optimization problem again until an optimal result is obtained. Lee et al. [23] integrated CPM into GA to develop an advanced stochastic time-cost tradeoff analysis. The CPM-guided GA improves computing efficiency by assigning the starting point of the search. Azad et al. [24] presented a design-driven heuristic approach termed guided stochastic search for minimum weight optimization of pin-hinged structures. This method was based on guiding the optimization process using the principle of virtual work to identify critical members.

When it comes to real-life large-scale steel buildings, illustrative examples are often limited to truss structures [14,25]. Liu and Ye [26] performed collapse optimization on moment-resisting domes with 744 beam-column members. Adeli and Sarma [13] conducted cost optimization on a 36-story moment-resisting steel frame. In these two moment-resisting examples, even though the number of structural members is large, the number of variables is dramatically decreased by member group strategy. Member group strategy takes one variable to represent a set of pre-selected members (usually similar members). It fails when the structure is irregular or subjected to unsymmetrical load. Moreover, this simplification distorts the mathematic model and the final result may be near-optimal rather than optimal. As for domes, stability is very sensitive to the section arrangement. A minor change of one member section may lead to a dramatic change of the stability capacity. Therefore, it's necessary to take each member as an independent variable for dome optimization against instability. In this case, the number of variables is equal to the number of structural members, leading to a real high dimension problem. Consequently, highly-efficient algorithms have become a dominant factor in the optimization of large-scale complicated buildings composed of beam-column members.

We conclude from this context that, there are two challenges involved in dome optimization against instability: a) representation of dome stability and b) a highly-efficient GA. A suitable representation of dome stability lays the theoretical foundation for optimization against instability. The highly-efficient GA functions as an approach to realize the optimization. A straightforward calculated representation of dome stability is conducive to a highly-efficient GA, and the highly-efficient GA depends, in turn, on the scientific formulation of the problem. However, stability (commonly defined in terms of linear eigenvalue buckling) is generally taken as the constraints in the optimization of real-life domes when stability is considered [27–30]. When the optimization is performed on simple structures composed of hinged-bars, nonlinear stability as represented in the energy approach is feasible to take as the constraints [31,32]. To our knowledge, an efficient optimization method aimed directly at maximizing the buckling load of large-scale real-life domes has not yet been reported in the literature. The reason lies in the lack of an instability mechanism for space domes. In addition, there is no simple yet suitable measurement to represent the stability of large-scale real-life domes except for the nonlinear critical buckling load P_{cr}, which precludes the formulation of optimization against instability.

In this paper, a new index, denoted as the relative gradient of joint well-formedness (gra_r), is defined to represent the stability of real-life large-scale domes from the perspective of joint well-formedness. The minimum value of gra_r, denoted as gra_r_{min}, measures the buckling load of a dome. The gra_r_{min} is a simple scalar that indicates the tendency to lose stability quantitatively rather than the ability to keep stable. Subsequent optimization against instability for maximum gra_r_{min} is established with discrete variables. Constraints on steel consumption and design requirements are implemented. Finally, a highly-efficient GA, termed the guided genetic algorithm (GGA), is developed to solve the optimization of real-life large-scale space domes composed of thousands of beam-column members. The structural response (gra_r of each joint) that is used for a fitness function is used again to identify critical members (vulnerable members & redundant members). Then in the mutation operation, only the genes corresponding to the critical members are altered so that vulnerable members are

strengthened and redundant members are weakened. The mutation is under the guidance of the instability mechanism, which is different from the existing random mutation commonly used by other researchers. The performance of the GGA is investigated using two real-life large-scale space domes (including a large-scale dome composed of 1122 beam-column members) to achieve the maximum buckling load. The optimal results demonstrate that the GGA is fast, efficient, robust and applicable in construction with a limited number of section types.

2. Representation of dome stability

An appropriate representation of an engineering system, as stated by Kicinger et al. [33], is one of the crucial elements of the GA. A satisfactory representation, which should take computational efficiency into consideration, represents a complicated engineering system in terms of a concise mathematical expression. For example, steel consumption, compliance and deformation are common representations of domes in optimization. Steel consumption corresponds to the cost of the dome, compliance represents the overall stiffness, deformation corresponds to the stiffness in a certain direction and nonlinear buckling load P_{cr} represents the dome stability. Compared with other indexes, P_{cr} consumes much more computational effort due to a nonlinear trace. Therefore, steel consumption, compliance and deformation rather than P_{cr} are widely adopted in dome optimization [34].

In this section, the relative gradient of joint well-formedness (gra_r) is defined to represent dome stability. The minimum value of gra_r is denoted as gra_r_{min}. In contrast to the ability of a dome to remain stable, gra_r measures the tendency to lose stability quantitatively. Hence, gra_r_{min} and P_{cr}, which offer an insight into stability from two opposite views, are both explicit representations of dome stability. In structural optimization, the response of structures subjected to loads is generally used to create an evaluation function for estimating the "fitness" of the generated solutions. This process usually consumes 85–95% of the total computational time [11]. In contrast to P_{cr}, gra_r as defined in this section is calculated with little computational effort. The straightforward-calculated gra_r, representing dome stability, will greatly shorten the computational time of fitness evaluation (see the examples in Section 5) and pave the way for optimization against instability of large-scale complicated domes.

2.1. Joint well-formedness

The global stiffness matrix **K** of a structure composed of n unconstrained joints can be expressed as an $n \times n$ partitioned matrix with each block matrix of the same order, i.e.,

$$\mathbf{K} = \begin{bmatrix} \mathbf{K_{11}} & \cdots & \mathbf{K_{1n}} \\ \vdots & \ddots & \mathbf{K_{kk}} & \vdots \\ \mathbf{K_{n1}} & \cdots & \mathbf{K_{nn}} \end{bmatrix} \tag{1}$$

where $\mathbf{K_{kk}}$ is the submatrix in **K** associated with joint j_k, $\mathbf{K_{kk}}$ is a symmetrical positive definite matrix, and its dimension c is equal to the number of degrees of freedom.

The well-formedness of joint j_k, denoted as q_{k0}, is defined in Eq. (2) in a scalar form to measure the overall stiffness of the joint.

$$q_{k0} = \det(\mathbf{K_{kk}}) = \prod_{i=1}^{c} \lambda_i \tag{2}$$

where $\lambda_i(i = 1,2…c)$ represents the eigenvalues of $\mathbf{K_{kk}}$.

According to linear algebra, the eigenvalues of $\mathbf{K_{kk}}$ represent the principal stiffness coefficients of joint j_k along the direction defined by the corresponding eigenvector [35]. From Eq. (2), the well-formedness