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Adaptive symbiotic organisms search (SOS) algorithm for structural design optimization

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Abstract

The symbiotic organisms search (SOS) algorithm is an effective metaheuristic developed in 2014, which mimics the symbiotic relationship among the living beings, such as mutualism, commensalism, and parasitism, to survive in the ecosystem. In this study, three modified versions of the SOS algorithm are proposed by introducing adaptive benefit factors in the basic SOS algorithm to improve its efficiency. The basic SOS algorithm only considers benefit factors, whereas the proposed variants of the SOS algorithm, consider effective combinations of adaptive benefit factors and benefit factors to study their competence to lay down a good balance between exploration and exploitation of the search space. The proposed algorithms are tested to suit its applications to the engineering structures subjected to dynamic excitation, which may lead to undesirable vibrations. Structure optimization problems become more challenging if the shape and size variables are taken into account along with the frequency. To check the feasibility and effectiveness of the proposed algorithms, six different planar and space trusses are subjected to experimental analysis. The results obtained using the proposed methods are compared with those obtained using other optimization methods well established in the literature. The results reveal that the adaptive SOS algorithm is more reliable and efficient than the basic SOS algorithm and other state-of-the-art algorithms.

Keywords: Truss optimization; Shape and size optimization; Symbiotic organisms search (SOS); Metaheuristic

1. Introduction

The design optimization of an engineering structure subjected to dynamic behavior is a challenging area of study that has been an active research area for many years. Thus, structural optimization with frequency constraints has been getting significant attention in the past decades. The fundamental natural frequencies of an engineering structure are extremely useful parameters to improve the dynamic behavior of the structure [25,34]. Therefore, some appropriate limits on the natural frequencies of the structure can help to avoid resonance with the external excitations [21]. In addition, engineering structures should be as light as possible, so as to make them cost effective [15,31,45]. On the other hand, weight reduction conflicts with the frequency constraints and induces difficulty in the structural optimization [44,47]. Therefore, an efficient optimization method is required to design the trusses subjected to fundamental frequency constraints and continuous efforts are put by the researchers in this direction.

Structural optimization can be broadly classified into two categories: discrete structural optimization and continuum structural optimization. Discrete structural optimization is also known as truss optimization and having connectivity of finite dimension parameters as variables (naturally discrete parameter system) and continuum structural optimization have field as a variable (discretized parameter system) [1,28,3,46,48]. The optimization of truss structure can be classified into three categories: size optimization, shape optimization, and topology optimization. Size optimization works to find the optimal element cross-sectional areas, whereas shape optimization works to find the optimal nodal positions of definite joints of the truss structure. The effect of shape and size variables on

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both the objective function as well as the related frequency constraints is fairly unlike [9]. Therefore, simultaneous shape and size optimization with multiple natural frequency constraints adds further complexity and often leads to divergence. Several researchers have employed various methods towards this end, yet this field has not been completely addressed so far. Bellagamba and Yang [4] introduced structural optimization with frequency constraints and later several researchers have been investigating further into this topic. Lin et al. [27] used a bi-factor algorithm based on the Kuhn-Tucker criteria. Grandhi and Venkayya [14] and Grandhi and Venkayya [39] tested optimality criterion (OC) based on the differentiation of the Lagrangian function. Wei et al. [40] introduced niche genetic hybrid algorithm (NGHA) by hybridizing the simplex search method and genetic algorithm (GA). Particle swarm optimization (PSO) was tested by Gomes [13]. Kaveh and Zolghadr [21] used charged system search (CSS) and enhanced CSS. Wei et al. [41] used parallel GA. Kaveh and Zolghadr [23] addressed hybridized CSS and big bang-big crunch (CSS-BBBC) with trap recognition capability. Miguel and Miguel [29] tested harmony search (HS) and firefly algorithm (FA). Kaveh and Zolghadr [19] utilized democratic PSO (DPSO). Kaveh and Zolghadr [20] compared the performance of nine metaheuristics. Pholdee and Bureerat [34] tested the comparative performance of 24 metaheuristics. Zuo et al. [49] applied hybrid OC-GA. Khatibinia and Naseralavi [24] presented orthogonal multi-gravitational search algorithm. Kaveh and Mahdavi [17] introduced colliding-bodies optimization (CBO). On the other hand, structural optimization with simultaneous static and dynamic constraints has been investigated by very few researchers [16,22,30,42].

Cheng and Prayogo [7] proposed a very promising metaheuristic algorithm, called the symbiotic organisms search (SOS) algorithm that is based on cooperating behavior among organisms in the nature. The SOS algorithm mimics symbiotic communication strategies that organisms use to stay alive in the ecosystem. The SOS algorithm is a population-based algorithm, where the organism of the ecosystem is considered as a population. The SOS algorithm prerequisites only common governing parameters such as population size and maximum number of function evaluations for its operation unlike the GA [49] requires mutation, crossover, selection rate, etc., the PSO [19] algorithm needs inertia weight, social, and cognitive parameters, and the HS [29] algorithm requires harmony memory rate, pitch adjusting rate, and improvisation rate [6]. However, the SOS algorithm does not require algorithm-specific controlling parameters, which makes the algorithm robust and generalize.

The SOS algorithm has been examined for constrained and unconstrained benchmark engineering problems and has proved to be a superior performer with other metaheuristics [6,7]. Cheng et al. [6] proposed the discrete SOS algorithm to optimize multiple-resources levelling problems. Capability of the SOS algorithm in the field of structural optimization is still under research; however, Cheng and Prayogo [7] have investigated the SOS algorithm for some structural optimization problems. The SOS algorithm works on three phases viz. the mutualism phase, the commensalism phase, and the parasitism phase. In the basic SOS algorithm, the benefit factor is decided through a heuristic step and it can be either one or two, which means that the organism gets partial or complete benefits from the interaction. However, in real practice, the organism may get benefits in any proportion. Moreover, Patel and Savsani [32,33] proposed a multi-objective improved teaching–learning based optimization (TLBO) algorithm with the use of adaptive control mechanism (viz. adaptive teaching factor) in order to enhance its capability. Automatically driven teaching factors has been improved the performance of the various algorithms in order to set a good balance between exploration and exploitation of the search space and to enhance the diversity of the population [10,2,26,32,33,35,36,38,43]. Therefore, the benefit factors (AB_1 and AB_2) of the SOS algorithm are improved to adaptive benefit factors (ABF_1 and ABF_2), which automatically tunes the value. This paper intends to investigate a good balance between exploration and exploitation of the search space. Therefore, we proposed three new versions of the basic SOS algorithm by considering all possible combinations of BF_1, BF_2, ABF_1, and ABF_2 in the basic SOS algorithm. It is also observed from the literature that the SOS algorithm has not been investigated for structural optimization with frequency constraints so far. These motives encouraged us to propose adaptability in the basic SOS algorithm and to investigate its effect on structural optimization problems.

2. The symbiotic organisms search algorithm

The SOS algorithm, proposed by Cheng and Prayogo [7], is a simple and powerful metaheuristic algorithm. The SOS algorithm works on the cooperative behavior seen among organisms in nature. Some organisms do not live alone because they are interdependent on other species for survival and food. The interdependency between two discrete species is known as symbiotic. In this context, mutualism, commensalism, and parasitism are the most common symbiotic relations found in the nature. Interdependency between two different species that results in mutual benefit is called mutualism. A relationship between two different species that offers benefits to only one of them (without the affecting other) is called commensalism. Finally, a relationship between two different species that offers benefits to one and cause harm to the other is called parasitism.

The SOS algorithm initiates with a randomly generated population, where the system has '*n*' number of organisms (i.e. population size) in the ecosystem. In the next stage, the population is updated in each generation '*g*' by 'the mutualism phase', 'the commensalism phase', and 'the parasitism phase' respectively. Moreover, the updated solution in the each phase is accepted only if it has a better functional value. The course of optimization is repeated until it satisfies the termination criterion. In this optimization method, the better solution can be achieved by the symbiotic relations between the current solution and either of other random solution and the best solution from the population.