Arabian Journal for Science and Engineering
https://doi.org/10.1007/s13369-025-10749-y

RESEARCH ARTICLE-MECHANICAL ENGINEERING

A Bacterial Chemostatic-Based Bio-Inspired Algorithm for the Structural Optimization of Planar Structures

Jersson X. Leon-Medina[2] · Juan F. Giraldo[3] · María A. Guzmán[1] · Jesús D. Villalba-Morales[4]

Received: 21 April 2025 / Accepted: 9 October 2025

Abstract

Topology optimization using bio-inspired algorithms has gained significant attention in recent decades, particularly for problems involving non-derivative search spaces. This paper introduces a novel bio-inspired algorithm for structural topology optimization, termed the bacterial chemotaxis-based topology optimization algorithm (BCBTOA). Inspired by bacterial chemotaxis, the method models material removal as a guided search process within a two-dimensional continuous domain, with the objective of minimizing structural compliance. To address common numerical challenges such as checkerboarding and mesh dependency, a chemotaxis-based regularization scheme is implemented. The algorithm requires only a single control parameter, R, which governs cavity size and material distribution. Numerical experiments on benchmark problems demonstrate that BCBTOA generates distinct, binary layouts without gray regions and produces mesh-independent solutions for optimal R values. Several communication models between artificial bacteria were investigated, with a modified exponential model yielding the best performance. In addition, different initialization strategies were evaluated, showing that random initialization consistently produced topologies with lower compliance. Overall, the algorithm achieves performance comparable to established methods such as sequential element rejection and admission (SERA) and soft bidirectional evolutionary structural optimization (BESO).

Keywords Topology optimization · Bacterial chemotaxis · Finite element method · Evolutionary structural optimization · BCBTOA

1 Introduction

Structural optimization is a well-established research field that integrates physical principles, mathematics, and computational methods to address the fundamental question: What is the optimal structural configuration to support a given set of loads under various constraints? To answer this question, the problem can be approached through three main strategies: size optimization, shape optimization, and topology optimization. The latter focuses on determining the optimal topology of a structure under specified conditions. For instance, topology optimization of trusses concerns structures composed of discrete elements connected at nodes. In such cases, the objective is to determine the optimal configuration of bars or members-often including their size, orientation, and connectivity-to efficiently carry the applied loads [1]. This category is particularly relevant in civil, aerospace, and mechanical engineering, where lightweight yet high-strength frameworks are essential. Truss optimization problems are typically formulated as discrete

✉ Jersson X. Leon-Medina
jersson.leon@uptc.edu.co

Juan F. Giraldo
juan.giraldo@csiro.au

María A. Guzmán
maguzmanp@unal.edu.co

Jesús D. Villalba-Morales
jesus.villalba@javeriana.edu.co

1 Department of Mechanical and Mechatronics Engineering, Universidad Nacional de Colombia- Sede Bogotá, carrera 30 calle 45, Bogotá 111321, Colombia

2 Escuela de Ingeniería Electromecánica, Universidad Pedagógica y Tecnológica de Colombia, Facultad Seccional Duitama, Carrera 18 con Calle 22, Duitama 150461, Colombia

3 Mineral Resources, Commonwealth Scientific and Industrial Research Organisation (CSIRO), 26 Dick Perry Ave, Kensington, WA 6151, Australia

4 Facultad de Ingeniería, Pontificia Universidad Javeriana, Carrera 7 No. 40 62, Bogotá 110231, Colombia

Published online: 03 November 2025

optimization tasks and have a long-standing history in structural engineering. While they often involve fewer degrees of freedom, they present significant combinatorial complexity [2]. In a broader context, topology optimization of continuous structures addresses the optimal distribution of material within a predefined design domain. Here, the structure is modeled as a continuum-typically analyzed using finite element methods [3]. This approach is widely applied to solid mechanical components and seeks to identify the best material layout to achieve specified performance objectives-such as minimizing compliance or maximizing stiffness-while satisfying constraints such as volume fraction or stress limits. With the continuous advancement of computational capabilities, topology optimization has become a critical tool in the design process across various disciplines, including structural mechanics, heat transfer, fluid dynamics, phononics, photonics, and beyond [4]. Recent research by Tang et al. [5], for example, reviews the application of topology optimization in advanced materials, such as composites and metamaterials. Consequently, the potential for enhancing designs across distinct yet interconnected domains has expanded significantly.

Binary topology optimization of structures, based on a finite element model, considers the presence or absence of material in each discretized element as the design variable. Mei et al. [6] optimized two-dimensional benchmark beams under concentrated loads by minimizing the strain energy while imposing volume constraints. Sivapuram et al. [7] addressed the topology optimization of microstructures in a two-dimensional space, aiming to maximize both bulk modulus and thermal conductivity. Setta et al. [8] optimized the topology of two-dimensional coated structures with the objective of minimizing heat compliance. Similarly, Mendoza et al. [9] optimized the topology of steel slotted dampers to maximize energy dissipation capacity, defining a two-dimensional material distribution. Although this formulation typically implies binary variables, the problem can be relaxed to allow elements to be partially filled with material-permitting design variables to vary continuously between 0 and 1. As noted by Bendsoe [10], interpolation functions and penalization strategies are employed in these relaxed formulations to discourage intermediate material densities and promote clear solid-void solutions. Topology optimization problems can be addressed using either derivative-based or derivative-free approaches, as discussed in the following sections.

Recently, several approaches have been proposed to develop gradient- or sensitivity-based methods for solving structural topology optimization problems. Huang and Xie [11] extended the Bi-directional Evolutionary Structural Optimization (BESO) method to simultaneously consider volume and displacement constraints. Munk et al. [12] emphasized that non-gradient-based topology optimization methods often rely on sensitivity functions to determine material removal or retention, with evolutionary algorithms ranking elements based on the magnitude of their sensitivity values. Ansola et al. [13] introduced the Sequential Element Rejection and Admission Method (SERAM), which combines sensitivity analysis with a mesh-independent filter. Liang and Cheng [14] addressed discrete-variable topology optimization using a sequential integer programming approach coupled with the Canonical Relaxation Algorithm, resulting in the development of the Discrete Variable Topology Optimization via Canonical Relaxation Algorithm (DVTOPCRA). Similarly, Picelli et al. [15] presented an implementation of the Topology Optimization of Binary Structures (TOBS) method, integrating binary design variables with gradient-based optimization and integer linear programming. In addition, several studies [16–18] have demonstrated improved efficiency in terms of iteration count, computational cost, and user accessibility, while also serving as valuable pedagogical tools for the field. In this context, Wang et al. [19] provide a comprehensive review of research in topology optimization, offering a useful entry point into the field.

The second option to tackle the problem is to use computational tools derived from artificial intelligence (AI), essential in the fourth industrial revolution [20]. Another comparison is made in the work of Páramo and Carrillo [21] where the Modified Simulated Annealing Algorithm (MSAA) is contrasted with the OC-SIMP [22]. The work concludes that the MSAA algorithm needs less computational time as the mesh becomes smaller. The HS algorithm was used in the study of Lee and Han [23] to solve TO problems and demonstrate better behavior compared to the ABCA and Bidirectional Evolutionary Structural Optimization (BESO) algorithms. It was found that fewer iterations are required to converge, showing good behavior in terms of stability, robustness, and convergence rate. Di Cesare and Domaszewski [24] combined the inverse-PageRank Particle Swarm Optimization and the Evolutionary Structural Optimization to consider simultaneously two objective, the minimization of the compliance and the volume. Radman [25] generated a hybrid algorithm from the BESO and Harmony Search to optimize the topology of the material microstructures, considering the homogenization theory and sensitivity analysis. Li et al. [26] applied Genetic Algorithms to the topology optimization of composite sound-absorbing structures, observing good capacities for global search. In the study of Deng et al. [27] developed a hybrid approach combining the Bat algorithm to explore the topology design space effectively and artificial neural networks to model the fitness landscape. Yuan et al. [28] presented a directed evolution algorithm tailored for non-gradient topology optimization. By iteratively ranking and replacing design candidates based on structural performance, the method mimics biological evolution without requiring sensitivity analysis. Furuta et al. [29] incorporated the Karhunen-Loeve expansion to turn computational feasible the application of an advanced differential evolution in the topology optimization of structures. Above results indicate that defining one algorithm for any topology problem is not an easy task, as each structural optimization problem generates a search space with particular characteristics. The No Free Lunch Theorems would support this affirmation.

In recent years, several novel metaheuristic algorithms have been introduced, including the Bacterial Colony Optimizer [30], the Exponential–Trigonometric Optimization Algorithm [31], the Puma Optimizer [32], and the p-Stochastic Global Optimization Algorithm [33]. The foundation of bio-inspired optimization (BiO) algorithms lies in modeling the behavior of living organisms and natural processes. Within this field, a number of methods are based on bacterial foraging mechanisms. Following the seminal paper by [34], the Bacterial Foraging Optimization Algorithm (BFOA) was introduced to solve optimization problems without requiring gradient evaluations of the objective functions. BFOA is a swarm-based technique inspired by bacterial chemotaxis and has been successfully applied to both global optimization [35] and multi-objective optimization problems [36]. Guo et al. [37] conducted a bibliometric analysis of the evolution of BFOA over two decades, showing that by 2021 more than one hundred variants had been proposed. Numerous applications have also been reported across diverse research fields. For example, Turanoglu and Akkaya [38] combined BFOA with simulated annealing to solve the facility layout problem. Manjula et al. [39] employed BFOA to determine optimal parameters for PID speed and current controllers in switched reluctance motors. Wang et al. [40] implemented BFOA to optimize collision-avoidance strategies in intelligent ships. Zaini et al. [41] developed an enhanced BFOA coupled with least-squares support vector machines to improve electricity load forecasting. In the area of shape optimization, [42] exploited the concept of bacteria migrating toward resource-rich regions to optimize the geometry of electromagnetic devices by relocating mesh nodes to more favorable positions. These diverse applications highlight the versatility and robustness of BFOA in addressing a wide range of optimization problems.

This work introduces an improved topology optimization (TO) algorithm based on bacterial chemotaxis, inspired by the formation of honeycomb-like patterns with solid regions and voids. The proposed Bacterial-Chemotaxis-Based Topology Optimization Algorithm (BCBTOA) incorporates the use of different initial structural configurations. Earlier conference papers- [43], [44], and [45]-laid the groundwork for applying the Bacterial Foraging Optimization Algorithm (BFOA) to topology optimization. Section 2 outlines the theoretical background, while Sect. 3 provides a detailed description of the proposed algorithm. Several numerical examples are presented in Sect. 4, addressing aspects such as mesh-size independence, convergence behavior, and parameter tuning. Additionally, the algorithm's performance was benchmarked against four established methods: Sequential Element Rejection and Admission (SERA) [13], Soft BESO [11], the Discrete Variable Topology Optimization via Canonical Relaxation Algorithm (DVTOPCRA) [14], and Topology Optimization of Binary Structures (TOBS) [15]. In this context, the main contributions of the present research are:

- Introduces a tailored application of the Bacterial Foraging Optimization Algorithm (BFOA) to solve the binary topology optimization problem for two-dimensional structures. The proposed approach integrates novel communication models among bacteria, problem-knowledge-based heuristics, and a criterion for defining solid and void elements by emulating bacterial movement toward more favorable locations in the environment.
- Demonstrates that the Bacterial-Chemotaxis-Based Topology Optimization Algorithm (BCBTOA) is competitive with established continuum topology optimization methods (SERA, Soft BESO, DVTOPCRA, TOBS), achieving lower or comparable compliance values across multiple benchmark problems.
- Provides evidence that BCBTOA produces binary, checkerboard-free topologies that are mesh-independent within appropriate parameter ranges, thereby addressing two of the most common numerical issues in topology optimization.
- Validates the robustness and adaptability of BCBTOA across different material volume fractions (50%–80%), showing consistent performance in scenarios with both limited and abundant material resources.

2 Theoretical Background for Topology Optimization and Bacterial Chemotaxis Pattern Formation

2.1 Problem Statement for Topology Optimization

The mathematical-computational approach known as Topology optimization (TO) allows finding the distribution of structural material in a given domain that better adapts to a design criterion (objective function). One typical objective function corresponds to minimization of compliance, **C**, which is obtained from the properties of the structure (global stiffness matrix, **K**) and the response of the structure (in terms of displacements, **U**) under the applied loads, **F**. The entire optimization formulation is stated in the following problem:

Fig. 1 Example of an optimized Michell type beam

$$
\begin{aligned}
&\underset{\mathbf{x}}{\text{minimize}} && \mathbf{C}(\mathbf{x}) = \mathbf{U}^T\mathbf{K}\mathbf{U} = \sum_{i=1}^{N} x_i\, \mathbf{u}_i^T \mathbf{k}_i \mathbf{u}_i, \\
&\text{subject to} && \mathbf{K}\mathbf{U} = \mathbf{F}, \\
& && \frac{V(\mathbf{x})}{V_0} = f_v, \\
& && x_i \in \{x_{\min}, 1\}, \quad i = 1, \ldots, N.
\end{aligned} \tag{1}
$$

where $\mathbf{x}$ is the design vector of size equal to N elements and values between $x_{\min}$ and 1, representing the presence of material or void in the i_{th} finite element, respectively. $\mathbf{u}_i$ and $\mathbf{k}_i$ are the displacement and stiffness to the element level. f_v is the initial volume fraction calculated as the ratio between the tested domain volume, $V(\mathbf{x})$, and the total domain volume, V_0. It is worth mentioning that the problem studied here is binary, with no possibility of intermediate densities.

To visualize the solution for a TO problem, Fig. 1 displays the optimized shape of a simply supported beam under a vertical load in the center known as Michell type beam when the algorithm proposed in this study is applied. Initially, the domain was a rectangular area filled with material. The black points in the figure represent the locations of the material in the optimized solution. The resolution of the image is determined by the size of the finite-element mesh. The following subsection presents three key factors for understanding the relationship between bacterial foraging and topology optimization, which forms the basis of the proposed method. It is worth noting that the bacterial foraging-based algorithm developed in this research is specifically tailored to the topology optimization problem and is not intended as a general-purpose optimization tool.

2.2 Bacterial Chemotaxis Optimization Mechanism

The time required for some organisms to search for food and other nutrients is significantly reduced when they form search groups, thereby simultaneously reducing their exposure to predation risks [46]. Individual bacteria move in small steps during foraging to acquire nutrients and avoid danger. The environmental conditions rule the bacterium movement, consisting of a forward motion and a rotational movement to change direction. This alternation of activities is called chemotaxis.

The iterative optimization process proposed in this study is based on moving the bacteria through routines of elimination and reproduction so that they are always positioned in areas with high nutrients (promising regions of the search space). The nutrients will die before the subsequent movements if one bacterium does not gather. To maintain the population size constant, they are replaced by the same number of healthy bacteria [47].

2.3 Chemotactic Strategy

The work of [48] shows the formation of patterns of a bacteria called Thiovulum Majus (TM); the microorganism creates mucus veils in the upper part of the marine sediments exhibiting regularly spaced patterns (honeycombs, interlaced bands or, reverse honeycombs). These patterns are simulated through a simple computational model based on the chemotaxis of oxygen and the ability of bacteria to induce advection of water when they are attached. Figure 2 shows the actual patterns that form the TM bacteria; they resemble a honeycomb with well-defined cavities and walls, while Fig. 2 shows patterns of intertwined bands. Figure 2b shows the simulated patterns of the TM bacteria such as combs (Fig. 2c), interlaced bands (Fig. 2d), or inverse combs (Fig. 2e). Recently, the formation of these patterns has been evidenced in works such as [49] and [50].

It is possible to use the chemotactic model explained in [48] to derive a method for TO due to their similarity. The mechanism of communication between bacteria is reproduced in such a way that they can identify areas of food (high compliance) or repel dangerous areas (low compliance) in a given domain (finite element model). Thus, the BCBTOA process will find cavities and determine the walls that make up the final structure.

2.4 Communication Model Between Artificial Bacteria

It is necessary to determine a strategy to consolidate the information of all the bacteria to guide the optimization process efficiently. Thar and Khul [48] propose a model to describe the communication process between bacteria. The original model for *Thiovulum majus* chemotaxis describes the colony behavior of bacteria qualitatively by mapping an environmental parameter $q(r)$ with a symmetric radial hat-shaped function (Fig. 3a), where r denotes the radial distance from the attached bacterium in an allowed maximum distance R. The regions most suitable for oxygen correspond to high values of $q(r)$. In TO, it is not possible to obtain negative values for the communication; thus, it is necessary to modify the hat-shaped function using the absolute values for $q(r)$ (Fig. 3b). This value $q(r)$ of each signal emitted by bacteria is calculated as the elemental compliance (C) multiplied by the

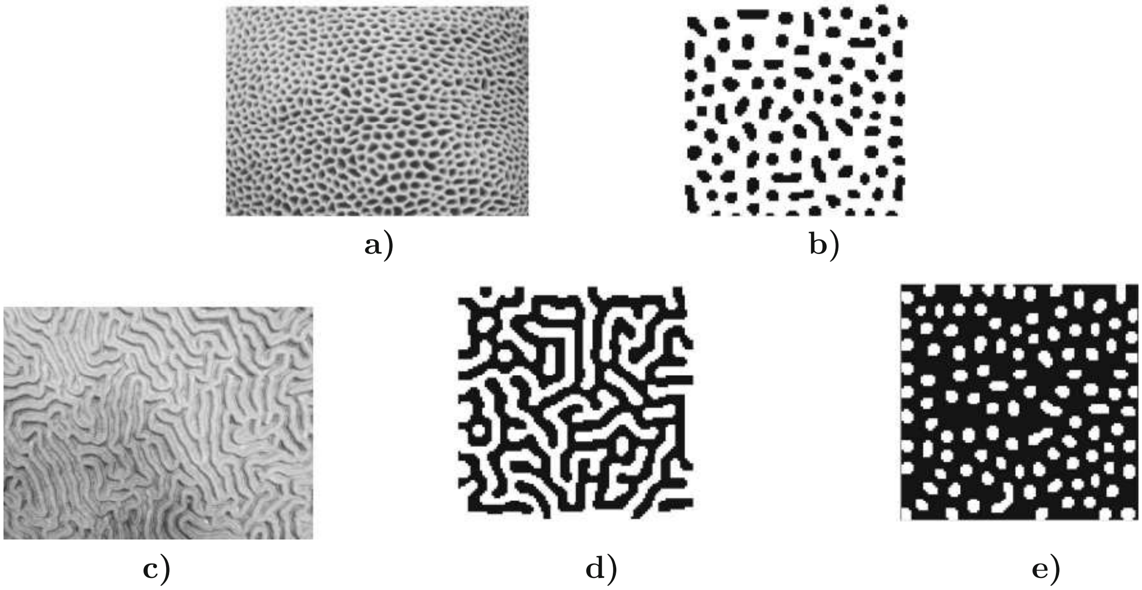

Fig. 2 Natural (**a**, **b**) bacteria patterns on sulfidic sediments and simulated (**c**, **d**, **e**) patterns with the mathematical model presented in [48]

value of the modified hat-shaped function, as shown in Eq. (2).

$$q(r) = \begin{cases} \left| C \dfrac{\sin\left(\frac{2\pi}{R} r\right)}{\frac{2\pi}{R} r} \right|, & \text{if } r \leq R \\ 0, & \text{if } r > R \end{cases} \tag{2}$$

A total environment parameter Q, at a specific location in the design domain, is calculated by adding all the $q(r)$ signals generated for bacteria whose influence reaches that location; see Fig. 4. The bacteria will be placed in positions with the maximum value of Q. Each bacterium will be located at the centroid of the element. It should be noted that the parameter r indicates the position relative to the midpoint; therefore, it is dimensionless. In case the mesh is not regular, it is recommended that the computation of parameter r considers a physical distance calculated in the geometry. Equation (2) must be consistent in the units used to guarantee that the result corresponds to those corresponding to compliance (C). Figure 4 shows the distribution of bacteria for three different volume fractions and their corresponding parameter Q calculated in Eq. (3).

$$Q = \sum_{i=0}^{M} q(r_i), \quad r \in [0, R] \tag{3}$$

where M refers to the number of elements found within the zone of influence given by $r < R$. It is worth mentioning that this strategy faces the checkerboard pattern in TO problems.

3 Topology Optimization Through Bacterial Chemotaxis Methodology

3.1 The Bacterial-Chemotaxis-Based Structural Topology Optimization Algorithm (BCBTOA)

BCBTOA follows an analogy with the self-organized movement of a bacteria colony to iteratively modify the topology of a structure until obtaining the optimized one for a specified load pattern. In this case, the compliance is selected as the quality measure, as given in Sect. 2.1. For plane structures, a 2D binary array, in close similarity with the finite element mesh, corresponds to the environment in which the bacteria colony moves (design domain), as shown in Fig. 5. It is observed that a set of bacteria occupies the elements or locations with the highest compliance. In this research, the void materials are considered as filled materials with very low density to avoid a process of re-meshing. The flowchart for BCBTOA is shown in Fig. 6, which is divided into four stages: 0) input data, i) total environment parameter computation, ii) bacteria movement, and iii) verification of the stop criteria. Stages i, ii, and iii are carried out iteratively. It is worth mentioning that the BCBTOA was implemented in MATLAB to test its performance. It was used the finite element solution given by reference [51].

The preliminary stage is carried out only once and consists of asking the user for the structural problem information and algorithm parameters. It is necessary to define the initial domain and the volume fraction (Volfrac) that would be used in manufacturing the structure. It is necessary to describe the characteristics of the finite element analysis, including the mesh size. It is necessary to show the independence of the