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RESEARCH ARTICLE

An Environmentally Adaptive CRO-SL Algorithm Based on Dynamic Agents for the Channel Assignment Problem in Wireless Networks

ANTONIO J. ROMERO-BARRERA[1], **LUIS CRUZ-PIRIS**[1], **MARINO TEJEDOR-ROMERO**[1], **JOSE MANUEL GIMENEZ-GUZMAN**[2], **AND IVAN MARSA-MAESTRE**[1]
[1]Departamento de Automática, Universidad de Alcalá, Campus Universitario, Alcalá de Henares, 28871 Madrid, Spain
[2]Departamento de Comunicaciones, Universitat Politècnica de València, 46022 Valencia, Spain

Corresponding author: Jose Manuel Gimenez-Guzman (jmgimenez@upv.es)

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ABSTRACT In recent decades, metaheuristic algorithms have emerged as indispensable tools for addressing complex optimization challenges, particularly in several engineering fields, where NP-hard problems are prevalent. A common NP-hard problem in communication engineering is the *Channel Assignment Problem* (CAP) for wireless access points (APs), with a determined number of stations (STAs) connected to them. The performance of the complete network depends on the interference and noise among the different clusters of devices and the obstacles or elements placed in the physical transmission space. To address the CAP, a new environmentally adaptive approach is proposed for the *Coral Reefs Optimization with Substrate Layers* (CRO-SL) algorithm, introducing new environmental agents: algae (representing tabu positions) and ocean water acidification (lowering fitness thresholds). The *Environmentally Adaptive CRO-SL* (EnvAdapt-CRO-SL) implementation aims to improve solution exploration, enhancing computational efficacy in generating new candidate solutions within the coral reef population. An exhaustive comparative analysis of four configurations of the proposed EnvAdapt-CRO-SL variant assesses the impact of each environmental agent on the algorithm's performance. Additionally, external benchmarks against four different metaheuristics, along with an analysis of the influence of pseudorandom number generators on initialization and search operators, and a robust optimization case study, provide deeper insights. The results show that incorporating the new environmental agents into the EnvAdapt-CRO-SL workflow significantly boosts throughput while reducing the computational time required to obtain optimal solutions.

INDEX TERMS Coral reefs optimization, EnvAdapt-CRO-SL, frequency assignment, graph modeling, wireless network.

I. INTRODUCTION

Nowadays, intelligent devices are an important part of our lives. One of the most used protocols for device communications is the standard IEEE 802.11 [1]. In 802.11 networks, frequency overlapping between channels considerably affects the communication performance of the connected devices. The *Channel Assignment Problem* (CAP) [2], [3], also named *Frequency Assignment Problem* (FAP) in other [4], [5], [6], is concerned as an optimization problem which objective is to establish the best distribution of wireless channels between each AP to minimize the total interference of the network and improve the final throughput of the device clusters.

In this context, metaheuristic algorithms have proven to be invaluable tools for addressing the intricacies of CAP [7]. These algorithms exhibit excellent behavior in exploring

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optimal solutions in large search spaces, offering a pragmatic approach to solving complex optimization problems. Despite the assurance that finding the global optimum is not guaranteed, the results derived from metaheuristic algorithms consistently demonstrate a remarkable proximity to the global optimal solution.

However, the landscape of randomized optimization algorithms has witnessed a surge in recent years, marked by an abundance of similar methodologies flooding the literature. Most of the contributions from the scientific community have collapsed the scientific journals, overshadowing and hindering advances in randomized optimization [8]. Despite the collected opinions, these bio-inspired proposals can be useful to provide a well-established benchmark to apply the environmentally adaptive design methodology proposed in our study. The conceptual metaphor theory [9], argues that metaphors are not simply ornaments of language, being fundamental tools to how we conceptualize and understand various abstract ideas and complex concepts.

Our approach shifts the focus towards modeling entire ecosystems by observing the relationships between different classes of individuals. This approach enables the generation of new stochastic procedures aimed at obtaining optimal solutions based on natural interconnected mechanisms between various species and their environments. Specifically, the environmentally adaptive methods we propose can be applied to enhance and extend several bio-inspired algorithms by integrating various agents within previously designed frameworks, replacing the isolated metaphors with an accurate representation of ecosystems.

In this vein, and understanding the problem characteristics presented previously, it seems clear that CAP is an ideal candidate to test the performance of the metaheuristic algorithms and their capacity to find optimal solutions in hardship domains. In order to address CAP, a new implementation of the *Coral Reefs Optimization with Substrate Layers* (CRO-SL) algorithm has been developed, based on the addition of two new agents within the classical algorithm's framework. To create an accurate evolutionary model of the behaviors observed in nature, it is essential to understand the relationship between the species of interest and the surrounding environment. The main purpose of this new version of the algorithm, named as *Environmentally Adaptive CRO-SL* (EnvAdapt-CRO-SL), is improving the search of solutions performance through the implementation of new stochastic procedures in the optimization process. Algae and acidification agents simulate two detrimental conditions for corals, creating a dynamic environment where several processes are intricately linked through mutual interaction.

To demonstrate the efficacy of this methodology, we conduct an analytical comparison between four standard population-based metaheuristic algorithms and three different configurations of the EnvAdapt-CRO-SL algorithm. The environmentally adaptive approach proposed in this study is rooted in the concept that behaviors observed in nature, when codified for optimization processes, derive their effectiveness from their interactions with other exogenous processes in the environment. This concept expands beyond the current paradigm of metaheuristics, emphasizing the modeling of the entire ecosystems rather than simply adapting isolated behaviors or processes.

This work provides the following contributions for the CAP study and CRO-SL algorithm development:

1) Review of previous works related to the CAP, in order to obtain a global vision about the optimization techniques used to face the frequency assignment of wireless devices.
2) Exploration of search landscapes for the CAP, seeking to define the topology of the problem solutions and verify its non-convex characteristics.
3) New dynamic environmentally adaptive methodology for ecosystem-based design of metaheuristics, applied to CRO-SL algorithm to address non-convex optimization problems with large search spaces.
4) Exhaustive comparison between three population-based metaheuristic algorithms with seven different configurations to face CAP.
5) Measurement of the initialization impact on the proposed environmentally adaptive version of the CRO-SL algorithm, through several tests comparing different Pseudorandom Number Generators (PRNGs).

This work is divided into a total of seven sections. In this section, a brief introduction to the topic of the study is exposed. A related work analysis is elaborated in Section II, to obtain information about optimization methodologies applied to wireless network problems. In Section III, explanations of theoretical frameworks of the CRO algorithm and the environmental methodologies proposals for the EnvAdapt-CRO-SL are presented. Section IV provides the mathematical background of the equations used in the fitness function to model the interference effects. Design process of the experimental tests and the research about the search landscapes described by CAP for a selected set of configurations are included in Section V. Results of the tests and conclusions are covered in Section VI and Section VII, respectively.

II. RELATED WORKS

A great controversy has been detected in the literature review regarding the design of metaheuristic algorithms. Several publications criticizing the metaphor-based metaheuristics can be found in recent years, reporting the saturation of academic articles that brand their new metaphor-based as novel, with the absence of rigorous benchmarking exacerbates this issue, as claims of algorithmic superiority remain unsubstantiated and ambiguous [10]. As it was discussed in [11] and [12], several evolutionary-based and swarm intelligence algorithms based their workflows on well-known methods such as the *Genetic Algorithm* (GA) or the *Particle Swarm Optimization* (PSO) algorithm, without making significant contributions. Some of the authors that follow this line have proposed automatic design methodologies for metaheuristics, that involve identifying optimal combinations of metaheuristic components and parameter settings to address specific optimization problems. Proposed approaches rely on two key components: a comprehensive design space encompassing all possible metaheuristic designs, and an Automatic Configuration Tool (ACT) facilitating exploration within this space [13]. This automatic selection methodology could be easily replaced by dynamic probabilistic methodologies for ensemble methods, allowing to choose of the final metaheuristic algorithm framework along the optimization process [14].

Concerning wireless network optimization, several heuristic approaches are set for a determined number of problems and, in several cases, they use specific rules of the problem to solve. In [15], a LR-based heuristic was used to solve a self-repairing load-balancing approach using mathematical programming and the Lagrangian relaxation method. The focus of the study is on minimizing delays and improving the Quality of Service (QoS) through adjustments in transmission power and association management for a Software-Defined Network (SDN).

Metaheuristic algorithms based on trajectories with non-deterministic exploratory behaviors, such as the version of the *Simulated Annealing* tested by the authors, can obtain quality solutions for CAP. Despite that, due to the non-convex properties of CAP, trajectory-based metaheuristics are not the best methodology to address these type problems, being necessary a laborious tuning of hyperparameters to show good performance [16].

Alternatively, metaheuristic algorithms based on population usually get better solutions for these type of problems. Evolutionary-based algorithms are a class of metaheuristics, in which frameworks are inspired by the evolution adaptability of individuals along different generations. The most popular algorithm of this class is the GA, of which one example of its applications in network problems was presented in [17], where authors investigate energy-restrained wireless networks. In that work, different configurations of hybrid genetic algorithms, with several types of crossover and mutation operators, were used to address a multi-objective optimization. The obtained results show relevant improvements in the increment of throughput, increasing the energy efficiency and minimizing the relative bit error rate, compared with similar models. Another frequently related technique is the evolutionary strategies such as the *Covariance Matrix Adaption Evolutionary Strategy* (CMA-ES). This optimization method was used in [18] to achieve the UAV IoT sensor throughput optimization, showing enhancements by optimizing the altitudes and distances from the ground base station.

Other types of metaheuristics commonly used to face wireless network problems are the swarm-based optimization algorithms. In the study presented in [19], a binary version of the *Whale Optimization Algorithm* (WOA) [20] was tested on different types of wireless networks resource allocation problems: mobile edge computation offloading and power allocation to improve the energy/spectral efficiency trade-off in wireless interference networks and the throughput maximization. Performance comparison between different types of swarm-based algorithms for network problems can be perused in [21] in which the authors compare an *Ant Lion Optimizer* (ALO) [22] with three other swarm-based algorithms such as *Moth Flame Optimization* (MFO) [23], *Ant Colony Optimization* (ACO) [24], and *Grasshopper Optimization Algorithm* (GOA) [25], to select the optimal cluster assignment for Wireless Body Area Networks (WBAN) oriented to implement an energy-efficient routing protocol for livestock monitoring activities.

In [26], graph coloring is applied to face CAP comparing common Wi-Fi channel selection tools. Authors focus the study on the comparison of diverse selection strategies in Wi-Fi networks: Least Interference (LI) and Beacon-based (LNB, LBP, and LBPm) channel selection techniques. There are other types of algorithms based on graphs, such as the proposed in [27] to optimize the Edge Weight Power and the Frequency Assignment (EWPFA) for dense cellular networks.

Several game theory methodologies have been applied to obtain optimal frequency assignments, as it is demonstrated in [28]. In there, the development of two decision-maker games is carried out to face a multi-objective representation of the FAP. In [29], a democratic negotiation system for decision-making is introduced, assessing two client-centric channel assignment approaches for addressing Wi-Fi channel selection.

Currently, Artificial Neural Networks (ANNs) are one of the most powerful tools for different research fields, and it is no different for wireless network investigations. A brief review of several use cases of Graph Neuronal Networks (GNNs) for communication networks is presented in [30]. Following this line, the study elaborated in [31] introduces a Random Edge Graph Neural Network (REGNN) for the wireless resource allocation problem. Numerical simulation results demonstrate higher performance of REGNN compared to other heuristics, emphasizing its transference capabilities. Another example of GNN uses for wireless networks can be found in [32], where authors propose a hybrid method of GNNs for optimal power allocation in ad-hoc wireless networks.

III. THEORETICAL FRAMEWORK OF THE ENVIRONMENTALLY ADAPTIVE CORAL REEFS OPTIMIZATION WITH SUBSTRATE LAYERS (ENVADAPT-CRO-SL)

This section explains the environmentally adaptive methods and the frameworks of the different CRO versions. In Section III-A, the methodology and steps for the environmental adaption of metaheuristic algorithms are presented. Subsequently, the standard CRO-SL and EnvAdapt-CRO-SL frameworks are exposed in Section III-B and Section III-C, respectively.

A. ENVIRONMENTAL ADAPTIVE METHODOLOGY

The environmentally adaptive methodology suggested in this paper is based on the elaboration of metaheuristic algorithms that simulate non-isolated behaviors and processes observed in nature. The evolution progress and behaviors of the species exist and work due to interconnected processes that relate them to their closer environment. This methodology supports the accurate modeling of environments and the assembly of real processes, leveraging past scientific investigations and established metaheuristic analogies. Next steps have been defined to adapt the framework of the algorithms:

1) Identify and formalize the isolation of a specific process for codification as a metaheuristic optimization algorithm.
2) Detect and investigate the exogenous factors influencing the identified process.
3) Evaluate and prioritize the most impactful external factors.
4) Adapt the algorithmic framework to incorporate the selected external factors as supplementary agents, integrating their interrelations to influence the solution search.
5) Elaboration of rigorous tests to measure the effects of these agents on the performance of the algorithm.

Several processes are involved in the natural ecosystems, and this fact is a disadvantage when it comes to modeling them in terms of computational efficiency. Numerous agents and relational processes could lead to a performance decrease with computational cost and quality of results. To avoid this problem, an adequate correlation between the size of the environment modeled for the algorithm must be set to limit the increase of the computational time required by the optimization procedures. In Figure 1, the proposed general framework of the environmentally adaptive design for metaheuristic algorithms is provided with a metaphor-free terminology [33]. In the agent-based algorithms, there can distinguish three different types of agents: neutral agents (solution population), beneficial agents, and harmful agents. Note that in certain cases, the frontier between beneficial and harmful agents could not be clear, acting as beneficial or harmful agents in function of the circumstances.

The proposed approach allows the framework extension of numerous existing population-based algorithms. In this work, we have chosen the CRO-SL algorithm to implement the environmentally adaptive methodology. Using this population-based algorithm, two new agents and their associated processes have been modeled and added within the original workflow of the CRO-SL algorithm.

The metaphor-free explanation of the designed environmental agents for the new CRO-SL proposal involves two key operators. First, the *tabu position* operator (algae) modifies the search process by restricting access to certain regions of the solution space, limiting the availability of open positions, and forcing solutions to compete for placement. This operator also introduces a location-based probability for eliminating solutions, with a higher likelihood of elimination in certain restricted areas. Second, the *gradual reduction of solution performance* operator (acidification) continuously reduces the fitness of solutions that have been present for longer, applying a progressively decreasing fitness threshold. This agent promotes the replacement of older solutions, preventing early convergence to suboptimal solutions and encouraging ongoing exploration throughout the search process.

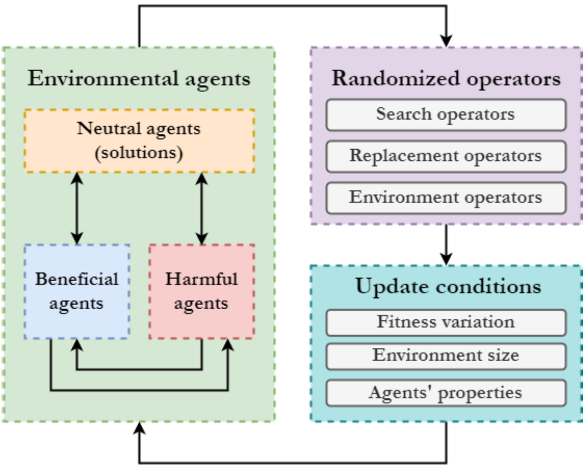


FIGURE 1. Metaphor-free framework of the environmentally adaptive design methodology.

It is important to introduce these environmental agents in a way that enhances algorithm efficiency rather than increasing computational cost. The *tabu position* operator reduces the number of available positions in the solution space, which means fewer search operators are executed as there are fewer solutions (corals) to process. This leads to a more focused and efficient search. Similarly, the *gradual reduction of solution performance* operator facilitates the replacement of older solutions by lowering the fitness threshold over time. This reduces the number of steps required for new solutions to replace older ones, speeding up the overall optimization process while maintaining exploration.

B. ORIGINAL FRAMEWORK OF THE CRO-SL ALGORITHM

The CRO algorithm is a metaheuristic approach, postulated in 2013 by researchers of the University of Alcalá, inspired by the processes observed in natural coral reef ecosystems [34]. Several articles and doctoral thesis [35], [36], [37], [38] have been focused on the development of new features for this algorithm. Based on these works, new versions of it have been appearing seeking to improve the original framework proposal, among which is the CRO-SL version. This ensemble methodology for the CRO was presented in [39], where two main stages of the algorithm's framework can be advised: *initialization phase* and *reef formation phase*.

1) INITIALIZATION PHASE

The first step covers the *initialization phase*. In this stage, the coral reef is represented as a matrix of size $n \times m$, where n denotes the number of positions on the reef and m corresponds to the total number of variables defined by the optimization problem for each solution. During the initialization process, some places of the reef are filled with corals based on the defined initial occupation rate. Each one of these corals is assigned to one substrate layer. The remaining positions are left empty, creating vacant holes within the reef structure. This initialization process sets the foundation for the subsequent exploration and optimization phases of the algorithm.

2) REEF FORMATION PHASE

The next step of the algorithm is the *reef formation phase*, during which main processes take place. In each generation, a significant portion of the corals undergo external sexual reproduction, where corals are selected to undergo broadcast spawn operators distributed across different substrate layers. Non-chosen corals for the prior reproductive process are subjected to internal sexual reproduction (*brooding*) through the application of mutation mechanisms to modify their variables, simulating self-fertilization in hermaphrodite corals. Following the reproduction processes, generated larvae undergo the *larvae settlement* step, involving larvae attempting to root and grow on the reef. A fitness-based tournament arises if the chosen position is already occupied, and unsuccessful attempts lead to depredation by the fauna of the reef. Asexual reproduction (*budding*), occurs in a small fraction of the best corals, which are replicated and mutated to be introduced to the larvae population. Finally, at the end of each generation, the depredation operator is randomly applied to a subset of corals with lower fitness values, generating new free positions on the reef that were previously occupied.

The CRO-SL algorithm represents an enhancement of the basic CRO framework, based on the application of ensemble methodologies, leveraging insights from real coral reef ecosystems and modeling the substrate composition and adult presence on reproduction and mortality patterns [40]. This algorithm operates following a competitive co-evolution strategy, wherein substrate layers encapsulate several processes, such as different operators, parameters, constraints, and selection functions. This design allows corals to undergo distinct processes during the reef formation phase, depending on their assigned substrate layer. Application of the substrate layer does not suppose any change in the codification of corals, only different search operators are used depending on the corresponding substrate layer of each coral.

In simpler terms, the introduction of substrates divides the reef into segments, accommodating specific operational frameworks. Corals evolve differently depending on the substrate assigned to them, incorporating different exploration operators. Despite that, there exists a small possibility of changing the substrate layer of the corals and the operator that modifies their structures. The efficiency of applying CRO-SL for constrained optimization has been demonstrated, achieving high-performance results in large-scale problems of diverse fields [41], [42], [43]. The adaptability given by the substrate layer operators makes the CRO-SL algorithm a potential tool to address complex optimization problems. Its ability to allocate different exploration algorithms into substrates contributes to its efficacy in optimizing solutions and solving problems with wide search spaces.

C. ENVIRONMENTAL DYNAMICS IMPLEMENTED IN THE ENVADAPT-CRO-SL ALGORITHM

New environmental agents have been introduced to the main framework of the CRO-SL algorithm to apply new dynamics that help to reduce the computational cost and improve the break out of stagnation states. The designed workflow of the EnvAdapt-CRO-SL algorithm is graphically described in Figure 2.

These agents stimulate exogenous environmental pressures on the core framework of the classical CRO-SL algorithm, leading to alterations in the intrinsic properties of the reef, such as the size of the reef or the probability of applying the substrate layers operators. This dynamic adaptation enhances the resilience of the algorithms, preventing long periods of stagnation and promoting the appearance of new candidate solutions from converged populations of corals. Added environmental agents stimulate the settlement of new larvae on the reef population through the application of several dynamic processes:

1) Set a dynamic fitness threshold that facilitates the replacement of old-rooted corals by new larvae through a random, continuous deterioration of the coral fitness value in each generation.
2) Establish a dynamic set of tabu positions that modifies the number of available positions on the reef, fostering a competitive behavior in the larvae due to the decrease in the hole number of the reef.
3) Intelligent selection of substrate, depending on the historical performance and the level of convergence of the corals in each generation of the reef.
4) Addition of an extra step in *depredation phase* that involves the algae population and its capacity to attract new predators to the reef, increasing the depredation probabilities depending on the coral proximity to each alga.

Parameters and data to make possible these dynamics are collected in two different structures, which are described by the following definitions:

1) **Algae:** new structure that contains the properties of one of the new agents, symbolizing algae colonization of some reef zones. This agent blocks some positions of the reef, fostering competitive behavior and the replacement of corals instead of automatic rooting in empty reef zones. Additionally, a global

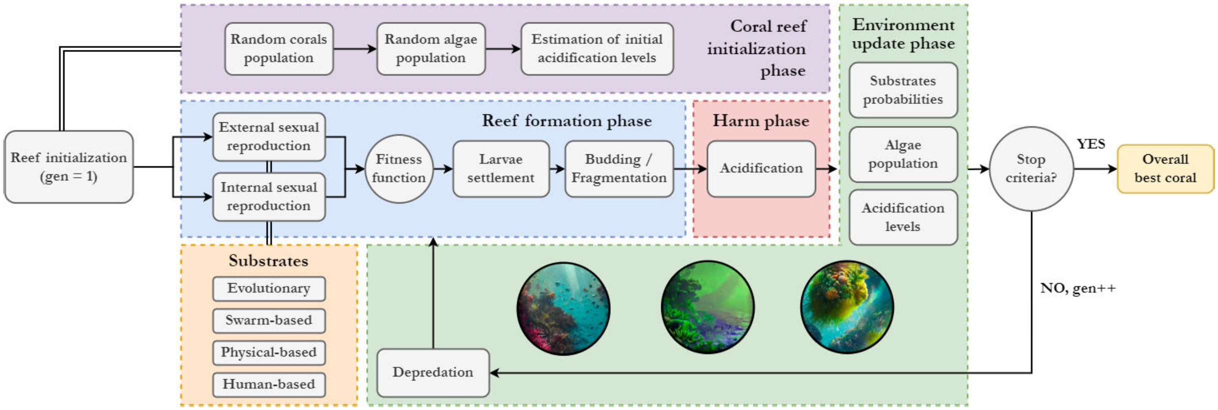


FIGURE 2. Framework of the EnvAdapt-CRO-SL algorithm.

probability of corals perishing is added in the depredation phase depending on the position of the reef and the proximity to algae, which increases the probability of being defeated by the reef fauna following a normal distribution.

2) **Acidification:** process that simulates the chemical water changes due to the increment of CO_2 and the decreasing of the pH (standard values for ocean water between $7.5 - 8.2$ [44]). A devaluation of corals along the iterations is established with the acidification pattern (continuous decreasing of the fitness value), harming the corals that have been set on the reef a while ago. A descending maximum fitness threshold is applied, promoting the breaking of coral population convergence.

Taking as reference the *Dynamic Probabilistic CRO-SL* (DPCRO-SL) presented in [14], an improved intelligent substrate selector is designed based on the association of operator tags for each substrate. By analyzing the influence of the new operators on the coral population, this method allows modeling a dynamic behavior for substrate selection based on successful larvae settlements. Substrates are divided into four classes: evolutionary, swarm-based, physical-based, and human-based. The probabilities of applying each substrate are updated along the iterations, depending on the coral population convergence and the previous participation in the generation of optimal larvae. Additionally, to improve the performance of the selection methodology, a coral variety review is implemented to detect the number of repeated solutions and the level of difference between them. By examining the coral population, a more efficient assignment of substrates can be carried out, i.e. applying a decreased penalty for the tag probabilities of crossover or swarm-based operators when the diversity in the coral population is low.

To encourage the variety of corals in the reef, a filter is applied to the population to select the repeated corals and, subsequently, these corals are subjected to a random selection process to determine which ones are eaten by the fauna of the reef. Additionally, an extra step in depredation operator is included, based on the coral's proximity to algae which host and attract predator species following a normal distribution, given by

$$p_d(k) = \frac{1}{n}\sum_{j=1}^{n_a} e^{-\frac{(k-x_a(j))^2}{2\sigma^2}}, \tag{1}$$

where x is the variable that represents the interest position, σ is the standard deviation, $x_a(j)$ is the j^{th} position of the algae set, n corresponds to the total number of positions on the reef and n_a is the amount of positions held by algae. Given a random-placed population of algae, an example of the depredation probability distribution for the reef position can be seen in Figure 3.

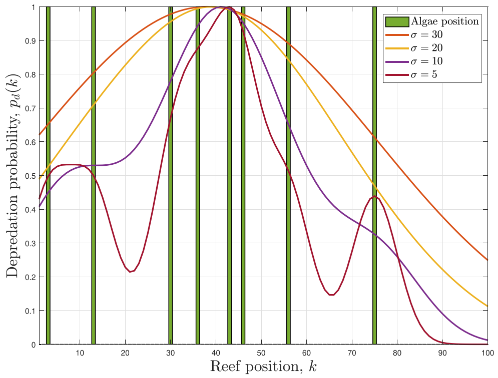


FIGURE 3. Algae proximity impact on depredation probability.

An additional interactive process is added when algae and acidification are both active. Algae population affects the grade of pH of the ocean water [45]. The acidification level at some position k of the reef ($A(k)$) is modeled using an adjustment factor λ and the common pH levels of ocean water, which their values are in the range between 7.5 and 8.2 [46], as

$$A(k) = 1 - \lambda \, \frac{|8.2 - \mathrm{pH}(k)|}{8.2}, \qquad \forall\, \mathrm{pH}(k), \lambda \in \mathbb{R} : \begin{cases} 7.5 \le \mathrm{pH}(k) \le 8.2, \\ \\ 0 \le \lambda \le 1, \end{cases} \tag{2}$$

where,

$$\mathrm{pH}(k) = -\log([\mathrm{H}^+](k)), \ \forall\, n_a \in \mathbb{Z}^+$$
$$\Rightarrow \begin{cases} [\mathrm{H}^+](k) = [\mathrm{H}^+]_0 - 2.53 \cdot 10^{-8} \dfrac{n_a}{n} \\ \left(\dfrac{2}{1 - \exp\left(\sum_{j=1}^{n_a} 1 - \frac{|k - x_a(j)|}{n} \right)} - 1 \right), \\ \ldots \text{for } 0 < n_a < n; \\ \\ [\mathrm{H}^+](k) = [\mathrm{H}^+]_0 = 3.16 \cdot 10^{-8}, \quad \text{for } n_a = 0. \end{cases} \tag{3}$$

As it is expressed in Equation (2), higher values of $A(k)$ represent lower acidification levels and less damage to the coral population. The decreasing evolution of the fitness value for a coral placed in the position k for each generation i is given by

$$f(\vec{x}_k)_{i+1} = A(k)_i \cdot f(\vec{x}_k)_i. \tag{4}$$

An example of the evolution of pH and $[\mathrm{H}^+]$ values for an ended reef position k as the number of algae population increases from two directional filling cases can be seen in Figure 4.

During the environment update phase, in which the algae population is modified, newly generated algae have associated a determined value of resistance (R_a) that defines the maximum number of iterations that they can be occupying a position. The quality of a reef position for the algae depends on the number of algae around that area, simulating the competitive behavior for empty zones to receive more sunlight. The initial resistance for a recently generated alga in function of the closer previous existing algae on the reef is denoted as

$$R_a(k) = (b + c) - \mathrm{size}(x_a(k) - b \le x_a(j) \le x_a(k) + c), \qquad \forall\, b, c, k \ne j \in \mathbb{Z}^+ : 0 < (j, k) \le n, \tag{5}$$

where range $[x_a(k) - b, x_a(k) + c]$ delimits the influence area of other algae in the rooting position k, n is the prior defined total reef size and $\mathrm{size}(x_a(j))$ denotes the number of existing algae positions in the analyzed portion of the reef. If the initial calculated resistance in one position is zero, no algae may root until the neighboring algae disappears.

IV. IEEE 802.11 SYSTEM MODEL

IEEE 802.11 set of standards, commercially known as Wi-Fi and elaborated by the Institute of Electrical and Electronics Engineers (IEEE), have become one of the most popular methods to build wireless access networks. These standards define two different operating modes: ad-hoc and infrastructure. On the one hand, ad-hoc mode enables direct communication between clients, and it is gaining popularity due to its application in IoT environments [47]. Despite that, most common Wi-Fi networks employ the infrastructure mode, in which the communication is established between an AP and an STA, not allowing direct information transmission between STAs. Within this defined infrastructure framework, Wi-Fi networks can be conceptualized as clusters of interconnected devices. Among the different generation or versions of IEEE 802.11 we can highlight IEEE 802.11n (Wi-Fi 4), IEEE 802.11ac (Wi-Fi 5), IEEE 802.11ax (Wi-Fi 6 and 6E), that can be considered the state-of-the-art, and IEEE 802.11be (Wi-Fi 7), that, based on Wi-Fi 6, is expected to be widely used in a near future. In this work, we propose an analytic Wi-Fi network model inspired in Wi-Fi 6, focusing on the 5 GHz frequency band and using 80 MHz channels, as it is a very popular choice. In Figure 5, we provide a representation of the channelization of the 5 GHz frequency band for different channel widths. As it can be shown, if we consider 80 MHz channels, we have six non-overlapping channels at our disposal.

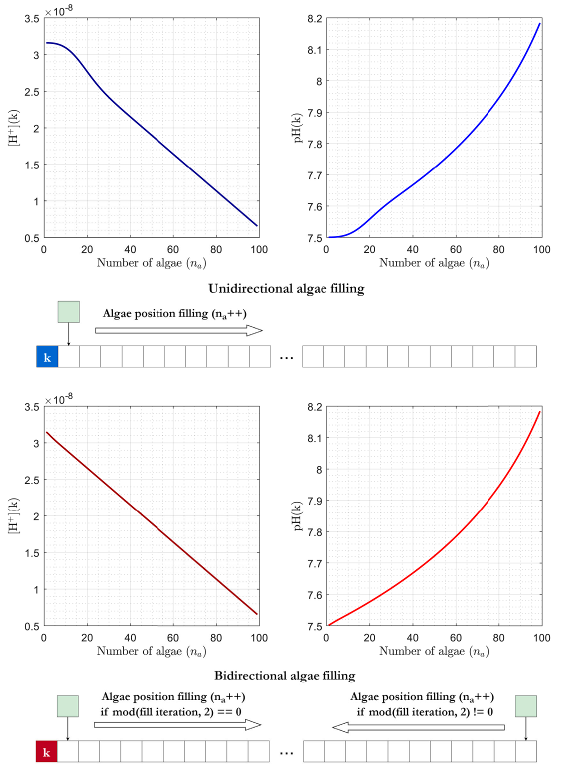


FIGURE 4. Evolution examples of pH and $[\mathrm{H}^+]$ values in a reef position k.

To account for the signal propagation, we have avoided the use of LOS channels or channel models that consider the effect of fast fading like Rician or Rayleigh channel models and, to better modeling the specific features of indoor signal propagation, we have resorted to the empirical model

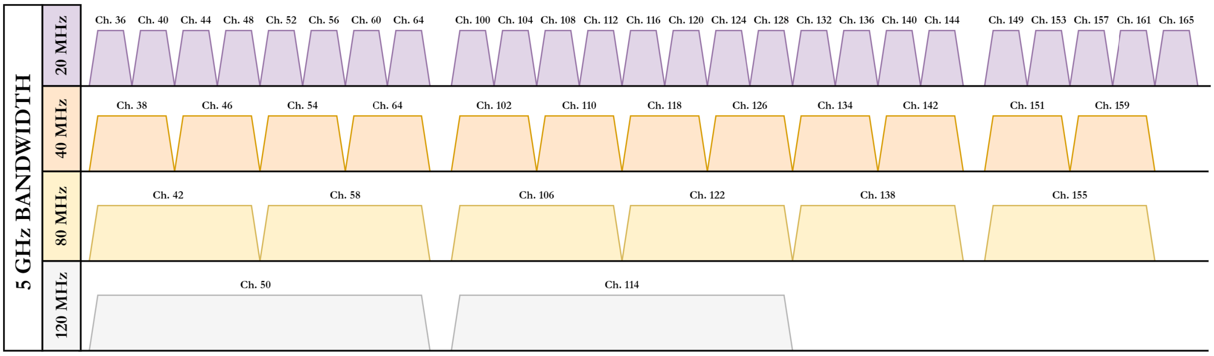


FIGURE 5. Non-overlapping channels for 5 GHz communications.

defined by the International Telecommunication Union Radiocommunication (ITU-R) model in its Recommendation P.1238-12 [48]. This model includes indoor transmission loss and considers losses when signals traverse different building floors. Propagation losses in dB are defined as

$$L_{\text{total}} = L(d_0) + N\log_{10}\left(\frac{d}{d_0}\right) + L_f(n_f). \tag{6}$$

The first component, $L(d_0)$ is the basic transmission loss, which depends on the frequency: $L(d_0) = 20\log_{10}(f) - 28$, where f is the frequency in MHz. The second component is the distance-dependent loss, where N is the distance power decay coefficient and d is the distance between transmitter and receiver in meters. Finally, the last component $L_f(n_f)$ is the floor penetration factor when the signal traverses n_f floors. Reference values of power loss are specified for residential environments in [49].

Using the Equation (6), the power of the signal received by a wireless device i from the signal transmitted by a different wireless device j can be calculated as

$$P_r^{j\to i} = P_t^j + G_j + G_i - L_{\text{total}}, \tag{7}$$

where P_t^j refers to the transmission power of the device j in dBm, and the transmission and reception gains of the antenna for devices j and i, measured in dB, are denoted by G_j and G_i, respectively.

In IEEE 802.11 networks, the throughput of an STA depends on the Signal-to-Interference-plus-Noise Ratio (SINR) measured at the receiver. Moreover, SINR depends not only on the power of the received signal but also on the power of other interfering signals from other devices operating in the same frequency channel, in addition to the thermal noise (N). Therefore, we can compute SINR as

$$\text{SINR}_i = \frac{P_r^{\mathcal{X}\to i}}{\sum_{j\in\mathcal{J}} I^{j\to i} + N}, \tag{8}$$

where J is the set of devices emitting interference signals (being $I^{j\to i}$ their power at the location of i), N denotes the power of thermal noise [50], and $P_r^{\mathcal{X}\to i}$ represents the power of the desired signal from $\mathcal{X}$ to i. The value of N can be estimated in function of the channel's bandwidth (Δf) denoted in Hz, through the following expression:

$$N = -174 + 10\ \log_{10}(\Delta f). \tag{9}$$

Finally, IEEE 802.11ax standard defines a set of Modulation and Coding Schemes (MCS) which, depending on the SINR, define the maximum achievable (nominal) throughput, as shown in Table 1. For example, for low SINR values, we can use modulations with a higher number of bits per symbol and higher coding rates, so the nominal throughput increases.

TABLE 1. MCS and throughput values for IEEE 802.11ax using 80 MHz channels with GI = 1.6 μ s.

MCS index	Modulation scheme	Coding rate	Throughput
0	BPSQ	1/2	34
1	QPSK	1/2	68.1
2	QPSK	3/4	102.1
3	16-QAM	1/2	136.1
4	16-QAM	3/4	204.2
5	64-QAM	2/3	272.2
6	64-QAM	3/4	306.3
7	64-QAM	5/6	340.3
8	256-QAM	3/4	408.3
9	256-QAM	5/6	453.7
10	1024-QAM	3/4	510.4
11	1024-QAM	5/6	567.1

Then, the throughput of an STA i for an MCS m for a certain SINR can be computed as

$$r_m^i(\text{SINR}_i) = \frac{L}{L+O}\, r_{m,max} \cdot \left(1 - P_e^{i,m}(\text{SINR}_i, L+O)\right), \tag{10}$$

with L the packet size, O the protocol overhead, $P_e^{i,m}(\text{SINR}_i, L+O)$ the packet error probability, and $r_{m,max}$ the nominal throughput for MCS m. Then, we choose the MCS that offers the highest throughput as

$$m^* = \underset{m\in\{0,\ldots,\mathcal{M}\}}{\arg\max}\ r_m^i(\text{SINR}_i), \tag{11}$$

being the throughput of STA i

$$r^i(\text{SINR}_i) = r_{m^*}^i(\text{SINR}_i). \tag{12}$$

V. DESIGN AND DEFINITION OF TEST EXPERIMENTS

With the aim of studying the algorithm behavior in order to address CAP, a series of experiments have been designed seeking to obtain comparative information about the performance of the EnvAdapt-CRO-SL proposals. An analysis of the search landscapes that describe the problem is carried out in Section V-B to verify the robustness of the solutions. The design of tests to measure the performance of solutions getting by EnvAdapt-CRO-SL and the impact of initialization on its capacity to obtain optimal solutions is described in Section V-C.

A. DEFINITION OF THE OPTIMIZATION PROBLEM

The CAP is concerned as a maximization problem in which the main objective is to find the optimal combination of channels for each AP distribution. CAP is framed as a network optimization, seeking to minimize the interference between closed STAs, maximizing the total throughput of the network.

Let G be a graph, denoted by $G = (V, E, w)$, where V represents the set of nodes, E expresses the set of edges and w constitutes the weight values associated with each edge. Nodes in V correspond to the defined APs and STAs in the network, with specific attributes including identifiers, labels, relative position, and type. The edges in E show the connections between nodes, characterized by the identification of the source and target nodes, while the associated weights quantify the distance between nodes. Using the graph data, the path losses model described in Section IV estimates the total throughput of the different clusters of devices.

The fitness function is defined as the sum of all throughput of the clusters. Given a channel distribution and one graph, which nodes represent the APs-STAs and edges the distance and relation between two nodes, the optimization CAP can be expressed as

$$\begin{aligned}
\text{maximize} \quad & f(\vec{x}, G)_{\vec{x}\in\mathcal{C}}, \\
\text{subject to} \quad & \mathcal{C} \subset \mathbb{R}^m, \quad \forall\, m \in \mathbb{Z}^+ : 0 < m; \\
& \mathcal{S} \subset \mathbb{R}^n, \quad \mathcal{S} = \{s_1, s_2, \ldots, s_n\}, \\
& \forall\, n \in \mathbb{Z}^+ : 0 < n \leq m; \\
& x_k \in \mathcal{S}, \\
& \forall\, k \in \mathbb{Z}^+ : 0 < k \leq m, \\
& (V_i, V_j) \in E \Rightarrow (V_i, V_j) = (V_j, V_i), \\
& \forall\, V_i, V_j \in V : i \neq j. \qquad (13)
\end{aligned}$$

where f corresponds to the fitness function, $\mathcal{S}$ represents the channel space set and $\vec{x} = [x_1, x_2, \ldots, x_m]$ is a channel distribution vector for m number of APs, belonging to the feasible solution subspace $\mathcal{C}$.

B. ANALYSIS OF CAP SEARCH LANDSCAPES

Search landscape exploration is an important technique to select the appropriate tools to face optimization problems [51]. Distance between solutions depends on the chosen codification of the problem, which can modify the search landscape representation of the solution schemes.

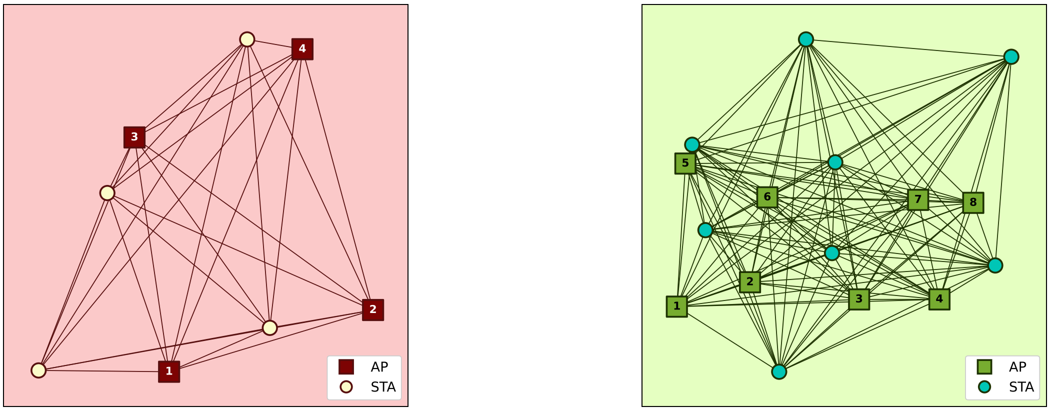
To accomplish the landscape search exploration, six problem configurations for two graph scenarios of four and eight APs are defined using three different channel spaces composed by the vectors hosted in the set $\{\langle 1, 2\rangle, \langle 1, 2, 3\rangle, \langle 1, 2, 3, 4\rangle\}$. Axis values for landscape representations are given by the splitting of the channel assignment in two different array partition schemes of the same size. Let $\mathcal{C}$ be the set of all channel distributions for a determined number of APs, then $\forall \vec{x} \in \mathcal{C}$, it holds that $\exists\{X_{ch}, Y_{ch}\}$ which satisfies $\vec{x} = [X_{ch} \mid Y_{ch}]$.

As we can see in Figure 6, the relation of the analyzed results for the example problem configurations tends towards a multimodal-type problem, wherein the search landscape representations contain numerous non-robust solutions. Search landscapes exhibit significant volatility in their values when the frequency distribution inputs are modified. This fact suggests that CAP is a NP-hard problem for large channel spaces and a great number of APs. As the search space increases due to the growth of the channel space or the number of APs, search landscapes show a rough surface and more pronounced volatility in closed environments for each one of the solutions.

This is an important fact at the time of selecting the type of metaheuristic algorithm to apply. Metaheuristic algorithms based on trajectories demonstrate a lower performance for high levels of multimodality [52], due to their inability to break stagnation states when a local optimum is reached, defining excessive exploitation practices. As an alternative, metaheuristic algorithms based on population show better capacity to explore the search landscapes and find better solutions continuously, benefiting from a large variety of search landscape positions as reference due to the parallel search elaborated by each individual (candidate solution).

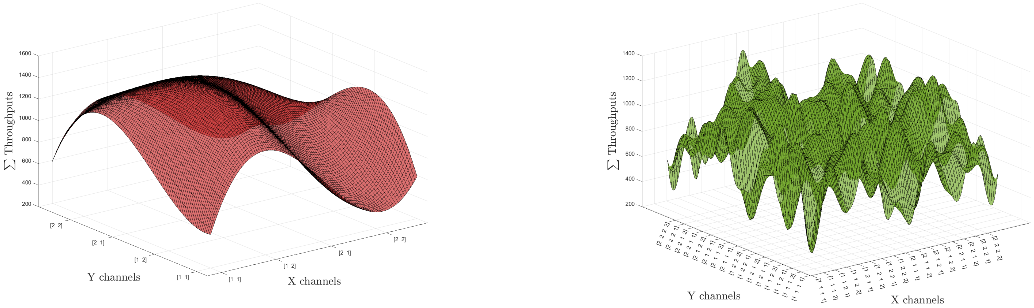
The simplest search landscape of the analyzed set of configurations is represented in Figure 6c. This configuration is a good example of the ideal search landscape for trajectory-based metaheuristic algorithms such as *Hill-Climbing* [53], *Gradient Descent* [54] or *Simulated Annealing* [55], which allow finding optimal solutions following the path settled by the best solutions of their closer environment. In the absence of local optima, these methodologies find the best solution for the problem, but in their presence, dependence on the initialization position becomes stronger.

Observing these facts, we have chosen two population-based algorithms to elaborate the performance comparison between them and the proposed EnvAdapt-CRO-SL algorithm. The selection of hyperparameters has been oriented to improve the search behavior of the substrates due to the noisy landscapes defined by the large combinations of channels and STAs. We have set high values for the acceleration coefficients in the PSO substrate and increased the number of mutable variables for mutation operators.



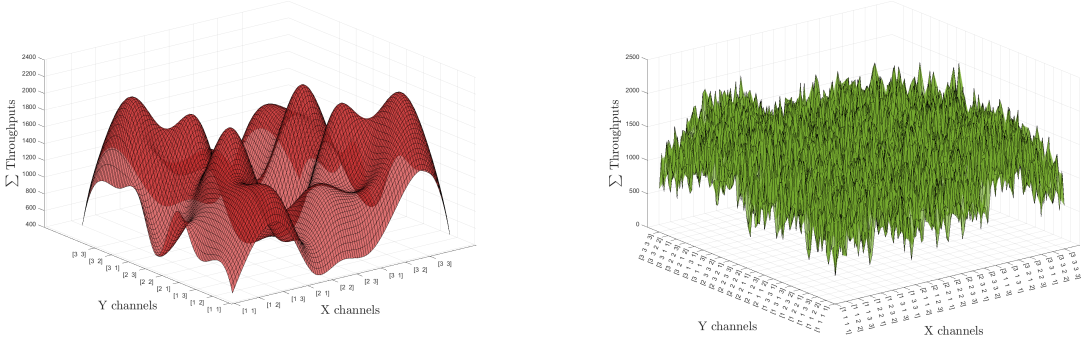
(a) Graph network of 4 APs - 4 STAs.

(b) Graph network of 8 APs - 8 STAs.



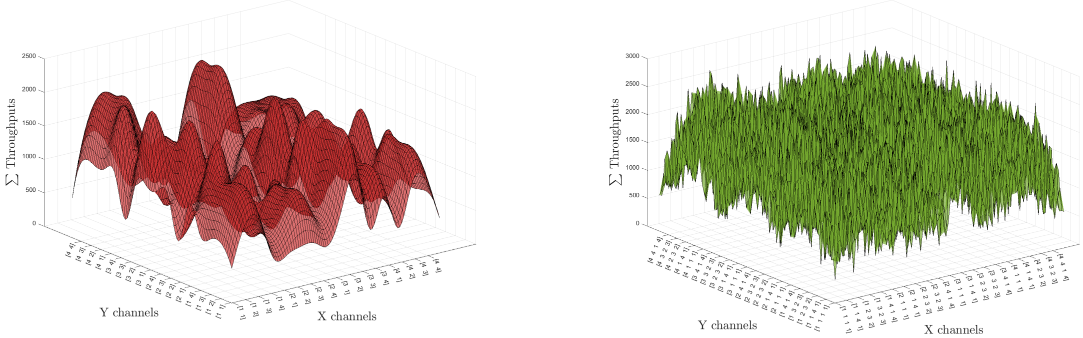
(c) Search landscape of 4 APs - 2 channels.

(d) Search landscape of 8 APs - 2 channels.



(e) Search landscape of 4 APs - 3 channels.

(f) Search landscape of 8 APs - 3 channels.



(g) Search landscape of 4 APs - 4 channels.

(h) Search landscape of 8 APs - 4 channels.

FIGURE 6. **Search landscapes for different problem configurations and scenarios.**

C. EXPERIMENTAL TEST DESIGN AND CONFIGURATION

Several test problems have been defined to elaborate precise performance comparisons between different configurations of EnvAdapt-CRO-SL algorithm and two population-based algorithms. The wireless network used for the test can be seen in Figure 7, where a multilayer graph network of a 5-floor building composed of 40 APs and 160 STAs is represented.

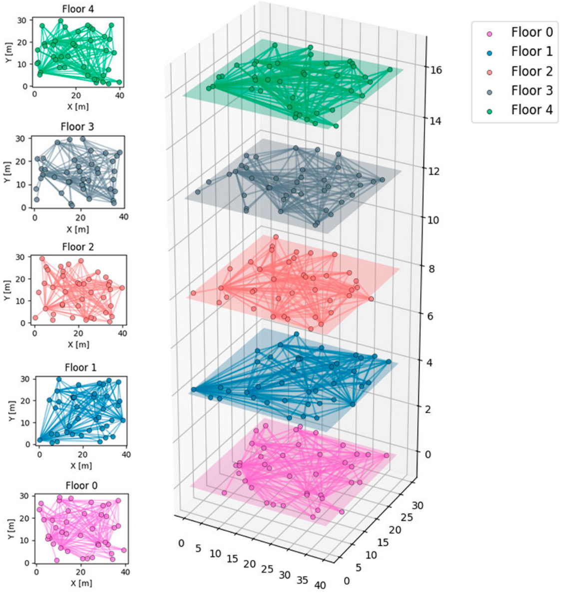


FIGURE 7. Multilayer graph of the device connectivity planar projections.

For the first test, four population-based algorithms (CRO-SL, GA, CMA-ES, and PRO) and one swarm-based algorithm (FFA) are used to optimize the assignment of a 5-values channel space for 40 APs that provide connection to a total of 160 STAs, distributed in five different interconnected graph layers. Descriptions of the mentioned algorithm have been collected in Section V-C1.

The second experimental test is focused on measuring the impact of the population initialization and pseudorandom generator process on the final quality of the solutions. Four Pseudorandom Number Generators (PRNGs) have been applied to compare their behavior generating initial populations of solutions and subsequent influence on the substrate layers during the optimization process.

The final experiment is oriented to study the robust optimization behavior and the impact of hyperparameter changes on the proposed environmental agents. In scenarios where solutions are applied to non-deterministic environments, uncertainty becomes a critical factor to account for [56], [57]. Several techniques can be used to solve this problem, a random scenarios maker has been created to generate 9 different buildings of three floors, hosting 24 APs fixed and 48 STAs in distinct positions. Nine random scenarios have been generated, as represented in Figure 12.

1) DEFINITION OF METAHEURISTICS FOR COMPARISONS

2) GENETIC ALGORITHM (GA)

One of the most popular methodologies for evolutionary optimization is the GA [58]. Its methodology was proposed by Holland [59], which is based on emulating natural selection processes, employing a population of individuals (candidate solutions), and applying several evolutionary operators, such as crossover and mutation. The operators modify the genes and chromosomes in which the individuals are coded, generating new offspring that attempt to replace the old individuals in the population.

Following the basic GA's workflow shown in Figure 8, the initial population has been modified using evolutionary operators that modify their structure's values. Subsequently, individuals undergo a process of selection, where individuals are chosen with a probability proportional to their fitness value. This process iterates multiple times within a loop, allowing the GA to explore and exploit the solution search space, seeking the optimal solution. The effectiveness of GAs lies in their ability to obtain robust and adaptable solutions to different classes of multimodal problem domains.

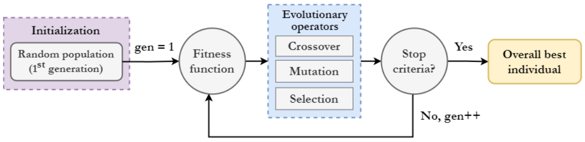


FIGURE 8. Framework of Genetic Algorithm (GA).

3) COVARIANCE MATRIX ADAPTATION EVOLUTION STRATEGY (CMA-ES) ALGORITHM

The CMA-ES algorithm is a stochastic optimization methodology that evolves a population of candidate solutions [60], [61], adapting both the mean and covariance matrix of a variable normal distribution of the population in each iteration.

The framework of the algorithm dynamically adapts its strategy parameters during the optimization process, including the population size (λ) and the number of parents (μ). Several parameters are employed such as recombination weights, cumulative constants, and sophisticated adaptation mechanisms for the covariance matrix and step size, ensuring an effective balance between exploratory and exploitative behaviors. The iterative process loop generates solution offspring, updates the evolution paths, and adapts the covariance matrix. The algorithm's loop ends after satisfying the stop criteria when the fitness reaches a predefined threshold or after a specified number of iterations. The workflow of the CMA-ES algorithm is represented in Figure 9.

4) FIREFLY ALGORITHM (FFA)

The FFA is a swarm-based metaheuristic optimization method introduced in 2008 [62], [63]. This algorithm is inspired by the natural behavior of fireflies, specifically

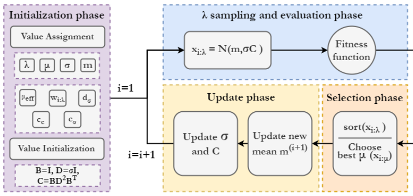


FIGURE 9. **Framework of CMA-ES algorithm.**

their bioluminescence, which plays a key role in their communication and attraction towards one another. In the context of the FFA, which framework is described in Figure 10, the brightness of each firefly symbolizes the fitness of a solution, and the movement of fireflies is governed by their relative attractiveness based on brightness. The algorithm describes a global communication pattern, where each firefly is attracted towards brighter fireflies, simulating a process of guided exploration in the search space, and progressively converging towards optimal or near-optimal solutions.

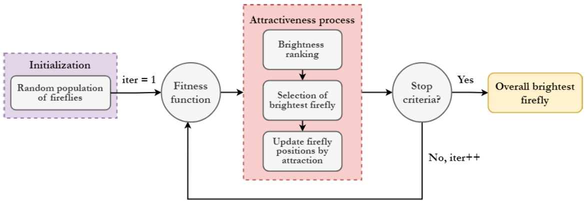


FIGURE 10. **Framework of Firefly algorithm (FFA).**

5) PARTIAL REINFORCEMENT OPTIMIZER (PRO)

The PRO is a relatively recent metaheuristic algorithm designed to address non-convex optimization problems by combining principles of reinforcement learning with evolutionary strategies [64]. Unlike traditional reinforcement learning methods, which typically rely on full environmental feedback, PRO uses a partial reinforcement mechanism. This means that generated solutions receive intermittent input regarding their performance, which adds a layer of exploration to the optimization process. As depicted in Figure 11, PRO implements a framework where each agent updates its behavior based on partial rewards from the environment.

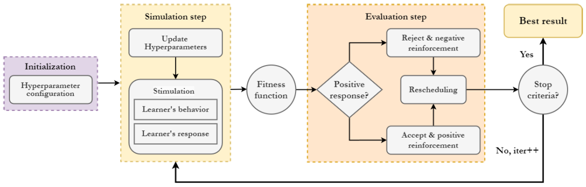


FIGURE 11. **Framework of Partial Reinforcement Optimizer (PRO).**

6) PSEUDORANDOM NUMBER GENERATORS

The initialization procedures of the problem have an important influence on the results obtained by the algorithms during the optimization process [65], [66]. One of the most popular methods to produce these arbitrary numbers is the PRNGs, which define pseudorandom arrays of float/double numbers using a seed number and a numerical sequence period for the generator [67]. To ensure the validity and reliability of the random number generator seeds, four PRNGs have been implemented on the tests to obtain a better measure of the initialization impact on the EnvAdapt-CRO-SL.

First of them is the Mersenne Twister (MT19937) generator, specifically its 32 bits version [68], which is a popular Generalized Feedback Shift Register (GFSR) algorithm [69], [70]. Another chosen PRNG for the comparative is the Multiplicative Lagged Fibonacci Generator (MLFG) [71], which uses a linear congruent methodology based on the Fibonacci sequence, seeking to improve the performance of other linear congruent PRNG.

The remaining two PRNGs follow a counter-based methodology. For the random value generation, the Threefry generator uses the Threefry algorithm [72], whereas the Philox Generator [72], [73] employs a generalized Feistel network [74].

7) DEFINITION OF THE APPLIED SUBSTRATE OPERATORS

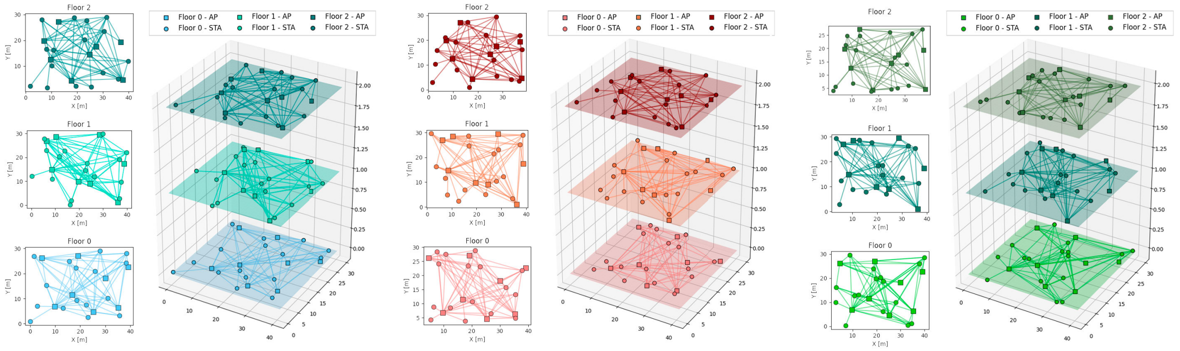
Previously to the test experiment evaluations, it is necessary to set the number of substrate operators that have been activated along the optimization process. In function of the reef size and the maximum allowed number of algae, the number of substrate operators will vary due to the number of corals needed to apply the operator's procedures. For instance, if the size of the reef is lower, it is more likely over the iterations that there will not be enough corals in a layer. This fact presents a challenge when applying crossover operators, which require two candidate solutions to be mixed, or swarm-based operators, which need several reference solutions to be followed.

To accomplish the test experiments defined in Section V-C, diverse operator classes have been selected from the evolutionary and swarm-based layers. Seven different substrates have been established for the EnvAdapt-CRO-SL framework to deal with the test experiments posed.

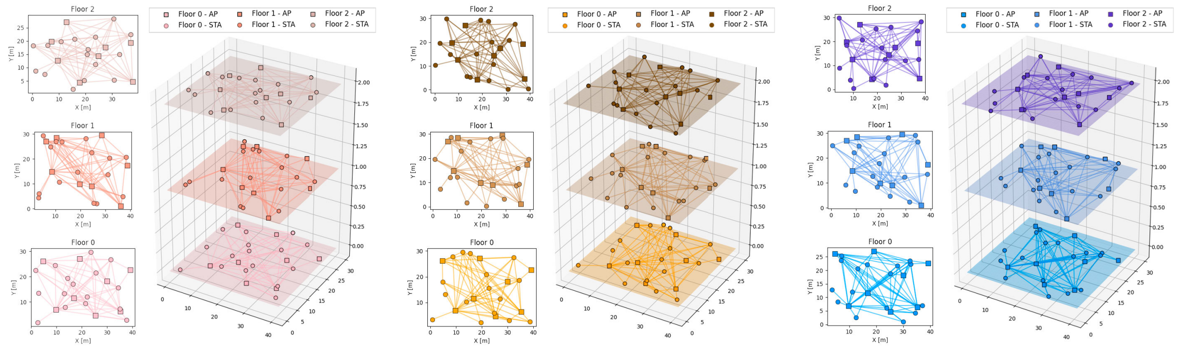
8) EVOLUTIONARY-BASED SUBSTRATES

Evolutionary-based substrates are divided into two types of operators depending on their processes to generate new candidate solutions: crossover and mutation. A total of four crossover typologies have been applied in the evolutionary-based substrates. The main differences between them are the number of crossover points and the method used to select the cut position, as can be seen graphically represented in Figure 13.

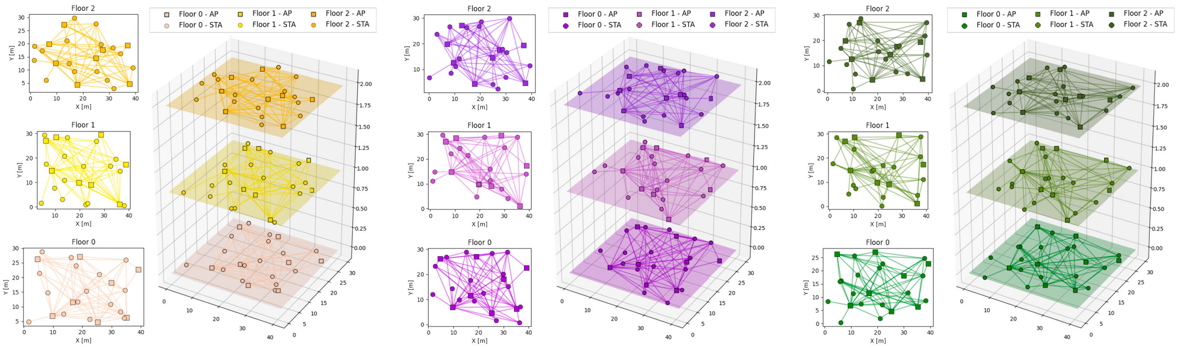
The evolutionary-based substrates incorporate four crossover methodologies. The *one-point crossover* (1Px) is a fundamental method that involves partitioning parental chromosome chains into two parts from a common section point, resulting in four divisions. The information from



(a) Scenario 1. (b) Scenario 2. (c) Scenario 3.



(d) Scenario 4. (e) Scenario 5. (f) Scenario 6.



(g) Scenario 7. (h) Scenario 8. (i) Scenario 9.

FIGURE 12. **Randomized STA's position scenarios for a 3-floor building.**

these divisions is mixed to generate two new offspring. In the case of the *two-point crossover* (2Px), the operator selects two section positions along the chromosome chains, swapping parental information between them to create two offspring. The *multi-point crossover* (MPx) stands out as the most exploratory methodology, selecting multiple crossover points in the chromosome chains of the parents. This results in two new offspring with genetic combinations that vary significantly from those of their parents.

The last crossover substrate implemented is the *blend crossover* α-β (BLX$\alpha\beta$) [75]. This substrate operator uses two real numbers as search amplitude parameters, α and β. Given these parameters, two new offspring (O1, O2) are generated by establishing a range between the gap interval (I_k) of the numerical values corresponding to the cross-point position (k) of each parent (P1, P2). The final values for these positions in the offspring vectors ($x_{\mathrm{O1,k}}, x_{\mathrm{O2,k}}$) are then randomly selected from the resulting uniform numerical range. The following expression defines the selection of values for the offspring variables at a position k as

$$x_{\mathrm{O1,k}} = \begin{cases} \mathrm{rand}(x_{\mathrm{P1,k}} - \alpha \cdot I_k,\ x_{\mathrm{P2,k}} + \beta \cdot I_k), \text{ if } x_{\mathrm{P1,k}} \leq x_{\mathrm{P2,k}}; \\ \mathrm{rand}(x_{\mathrm{P2,k}} - \beta \cdot I_k,\ x_{\mathrm{P1,k}} + \alpha \cdot I_k), \text{ if } x_{\mathrm{P1,k}} > x_{\mathrm{P2,k}}. \end{cases}$$
$$x_{\mathrm{O2,k}} = \begin{cases} \mathrm{rand}(x_{\mathrm{P1,k}} - \beta \cdot I_k,\ x_{\mathrm{P2,k}} + \alpha \cdot I_k), \text{ if } x_{\mathrm{P1,k}} \leq x_{\mathrm{P2,k}}; \\ \mathrm{rand}(x_{\mathrm{P2,k}} - \alpha \cdot I_k,\ x_{\mathrm{P1,k}} + \beta \cdot I_k), \text{ if } x_{\mathrm{P1,k}} > x_{\mathrm{P2,k}}. \end{cases} \quad (14)$$

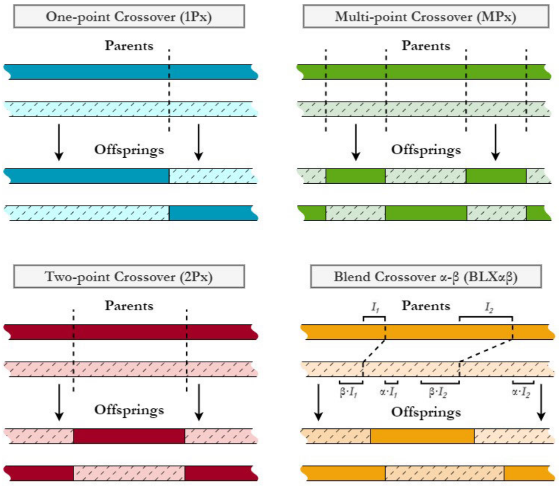


FIGURE 13. Crossover operators used in evolutionary-based substrate layers.

Regarding the mutation operators, three different mutation substrates have been used to apply random variable modifications to the structure of the corals. Gaussian mutation (GM) is a technique that perturbs the values of coral variables by adding random magnitudes sampled from a Gaussian distribution [76]. Random mutation (RandM) involves modifying a small fraction of coral's variables, changing their values to other random magnitudes within the established boundaries. Additionally, shuffle mutation (ShuffleM) involves the random permutation of values between paired positions of the coral's variables.

9) SWARM-BASED SUBSTRATES

Swarm intelligence is one of the most emulated methodologies to address complex optimization problems. Selected swarm-based substrate uses techniques taken from the most popular algorithm of this class, the *Particle Swarm Optimization* (PSO) algorithm, which is inspired by the social behaviors observed on the displacement of groups of animals such as birds or fishes [77]. Paths described by the particles along the iterations are under the influence of the best particle's coordinates (x_g^{best}) and the best personal position reached in their movement record (x_p^{best}). The following motion equations define the movement behavior of the particles using the two mentioned point references as

$$(\vec{x}_{i+1}, \vec{v}_{i+1}) = \begin{cases} \vec{x}_{i+1} = \vec{x}_i + \vec{v}_{i+1}, \\ \vec{v}_{i+1} = w\,\vec{v}_i + c_1\,r_1\,(\vec{x}_p^{best} - \vec{x}_i) + \\ \qquad\qquad c_2\,r_2\,(\vec{x}_g^{best} - \vec{x}_i), \end{cases} \tag{15}$$

where $\vec{v}$ are the velocity vectors in an iteration i, w is the inertia value, $\langle r_1, r_2 \rangle$ are two unitary random values and $\langle c_1, c_2 \rangle$ represent the cognitive and social coefficients, which both define the influence of the different reference points on the calculation of $\vec{v}_{i+1}$.

VI. OPTIMIZATION RESULTS AND DISCUSSION

A. PERFORMANCE COMPARISON BETWEEN POPULATION-BASED ALGORITHMS FOR CAP

A detailed comparison between a swarm-based approach and four population-based metaheuristic algorithms is conducted. The population-based evaluation includes four configurations of CRO-SL, two configurations of GA, and the CMA-ES, while the selected swarm-based algorithm is the FFA. As it was exposed in Section V-C, the experimental design employed in this test involves comparing several random seeds for MT19937 to measure the impact of the problem initialization in different metaheuristic algorithms. Values of the results obtained from the optimization processes can be consulted in Table 2.

Obtained results denote a good-quality performance of the crossover operators to increase the throughput value of the solutions, despite that, it is needed to combine these crossover operators with other types of operators to create a high variety of individuals in the population. Low numbers of the iterations at which the optimal solution was found indicate a fast convergence but worse behavior to escape from population stagnation conditions. In this experiment, CRO-SL configurations show better capacity to add diversity to their populations of solutions in comparison with GA and CMA-ES algorithms, in which replacement rates are notably lower. The remaining two algorithms, FFA and PRO, exhibit similar average throughput results to those of CMA-ES, characterized by lower average throughput values and higher standard deviation. This indicates less consistent performance across iterations, with greater variability in their throughput outcomes.

Fast convergence methods are well received for static stop criteria with a low number of iterations or dynamic stop criteria in which the end of the optimization loop depends on the number of stained iterations. Obtained average throughput values prove the enhancement of the algorithm with the addition of environmental agent structures to the classical workflow of the CRO-SL algorithms.

It is important to note that a higher number of fitness calls negatively impacts performance, as the objective function is the most computationally expensive part of the process. As can be seen, the introduction of environmental agents reduces the number of calls to this function, thereby improving the results and reducing computational overhead.

The consistency of the metaheuristic algorithms is an important factor in reducing the impact of the random processes linked to the search operators. Acceptable throughput standard deviation values are achieved by EnvAdapt-CRO-SL configurations compared to the other algorithms, describing a low level of volatility between its optimal solutions. An opposite example of this behavior was presented by CMA-ES, which, although it obtained the best overall distribution of channels for seed 153, its remaining results are poor quality compared to the values obtained by the other tested algorithms.

TABLE 2. Performance comparison between different configurations of population-based metaheuristic algorithms (PRNG: MT19937).

Algorithm	Seed	Iteration	$\sum$Throughput	Objective Function Calls	Replacement rate	Max. iteration	Statistics	
CRO-SL	0001	334	50063.65	222471	0.2403	500	**Avg. $\sum$ throughput**	50039.06
	0153	478	50820.83	316361	0.1252	500	**Mean replacement rate**	0.2865
	2948	85	49161.13	60115	0.4423	500	**StD. throughput**	563.08
	5991	161	49938.89	109748	0.2955	500	**StD. replacement rate**	0.1284
	7002	388	50423.23	259454	0.1875	500		
	9527	121	49826.62	95879	0.4283	500		
EnvAdapt-CRO-SL($*$)	0001	240	50396.41	148675	0.2552	500	**Avg. $\sum$ throughput**	50000.63
	0153	362	49911.28	238784	0.1613	500	**Avg. replacement rate**	0.2647
	2948	173	49872.44	135642	0.2788	500	**StD. throughput**	238.70
	5991	156	50035.07	97815	0.3636	500	**StD. replacement rate**	0.0832
	7002	52	49818.43	35367	0.5872	500		
	9527	179	49970.16	120813	0.3020	500		
EnvAdapt-CRO-SL($^{\diamond}$)	0001	319	50095.66	251115	0.6360	500	**Avg. $\sum$ throughput**	50176.81
	0153	418	50027.42	277839	0.4987	500	**Avg. replacement rate**	0.5581
	2948	317	50026.09	210944	0.5011	500	**StD. throughput**	122.74
	5991	72	50286.44	50584	0.5965	500	**StD. replacement rate**	0.0691
	7002	363	50484.38	239494	0.5459	500		
	9527	81	50140.84	64726	0.6381	500		
EnvAdapt-CRO-SL($*^{\diamond}$)	0001	117	50482.03	91064	0.6282	500	**Avg. $\sum$ throughput**	50429.18
	0153	239	50077.86	185189	0.6178	500	**Avg. replacement rate**	0.5719
	2948	426	50170.99	260218	0.4477	500	**StD. throughput**	262.13
	5991	66	50475.48	50885	0.6392	500	**StD. replacement rate**	0.0811
	7002	404	50780.04	245687	0.4918	500		
	9527	447	50588.66	349913	0.6066	500		
GA (1Px)	0001	38	50226.83	38000	0.4098	500	**Avg. $\sum$ throughput**	50179.59
	0153	59	49758.53	59000	0.3300	500	**Avg. replacement rate**	0.1816
	2948	111	50036.08	111000	0.1500	500	**StD. throughput**	341.94
	5991	422	49945.75	422000	0.0600	500	**StD. replacement rate**	0.1520
	7002	463	50709.57	463000	0.0500	500		
	9527	221	50400.79	221000	0.0900	500		
GA (2Px)	0001	238	50538.25	238000	0.0906	500	**Avg. $\sum$ throughput**	50321.71
	0153	73	50430.58	73000	0.3032	500	**Avg. replacement rate**	0.2381
	2948	493	50015.05	493000	0.0408	500	**StD. throughput**	176.65
	5991	80	50349.54	80000	0.2560	500	**StD. replacement rate**	0.1414
	7002	30	50272.10	30000	0.3850	500		
	9527	47	50324.76	47000	0.3529	500		
CMA-ES	0001	104	48176.41	104000	N/A	500	**Avg. $\sum$ throughput**	48823.03
	0153	93	51239.74	93000	N/A	500	**Avg. replacement rate**	N/A
	2948	99	46849.10	99000	N/A	500	**StD. throughput**	1515.14
	5991	96	48915.69	96000	N/A	500	**StD. replacement rate**	N/A
	7002	108	48069.75	108000	N/A	500		
	9527	108	49687.48	108000	N/A	500		
FFA	0001	29	47145.91	29000	N/A	500	**Avg. $\sum$ throughput**	48158.41
	0153	15	49297.46	15000	N/A	500	**Avg. replacement rate**	N/A
	2948	32	48889.89	32000	N/A	500	**StD. throughput**	1290.38
	5991	18	48725.87	18000	N/A	500	**StD. replacement rate**	N/A
	7002	22	48790.29	22000	N/A	500		
	9527	18	45899.04	18000	N/A	500		
PRO	0001	473	47000.74	473000	N/A	500	**Avg. $\sum$ throughput**	47341.93
	0153	429	47509.31	429000	N/A	500	**Avg. replacement rate**	N/A
	2948	498	48472.21	498000	N/A	500	**StD. throughput**	607.69
	5991	495	47240.90	495000	N/A	500	**StD. replacement rate**	N/A
	7002	411	47048.38	411000	N/A	500		
	9527	470	46776.03	470000	N/A	500		

Note: ($*$):=acidification, ($^{\diamond}$):=algae, ($*^{\diamond}$):=acidification + algae.

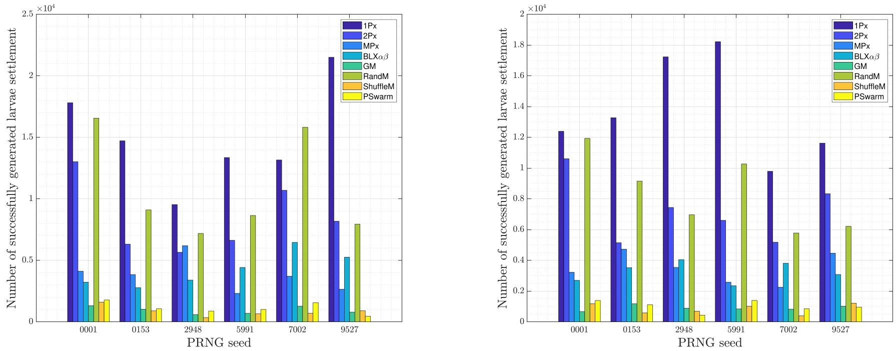
In terms of substrate performance, as it can be seen in Figure 14, layers based on evolutionary operators exhibit a higher engagement in the larvae settlement process. The participation values of the random mutation substrate stand out significantly compared to the other mutation substrates. This phenomenon arises from the elevated complexity that characterizes the search landscape of the problem. The presence of several local maxima and minima encourages extensive exploratory behaviors, thereby penalizing exploitative substrates such as GM or shuffle mutation.

Regarding the crossover substrates, 1Px is the most conservative crossover methodology, being more demanded than the remaining cross operators. This fact denotes that abrupt changes in the channel distribution, carried out by establishing several cross points, hinder the reach of optimal fitness values for the generated larvae population. Despite the good behavior shown by the random mutation operator, it is relevant to appoint that the established variable range threshold of the feasible solution search space is low, and this operator will lose effectiveness as the variable value threshold increases. Finally, as expected after seeing the behavior of the FFA, the PSO-based substrate shows low participation in the rooting of solutions in the reef compared to the other substrates mentioned. The poor performance of the swarm-based algorithms in generating high-quality solutions for the given problem is attributed to the limited range of values that the decision variables can take, making it a suboptimal choice for this type of problem. This outcome aligns with the No Free Lunch (NFL) theorem, which states that no single algorithm performs optimally across all problem types, emphasizing the need to select algorithms tailored to specific problem characteristics [78].

B. INFLUENCE OF PRNGs ON THE CAP INITIAL SOLUTIONS

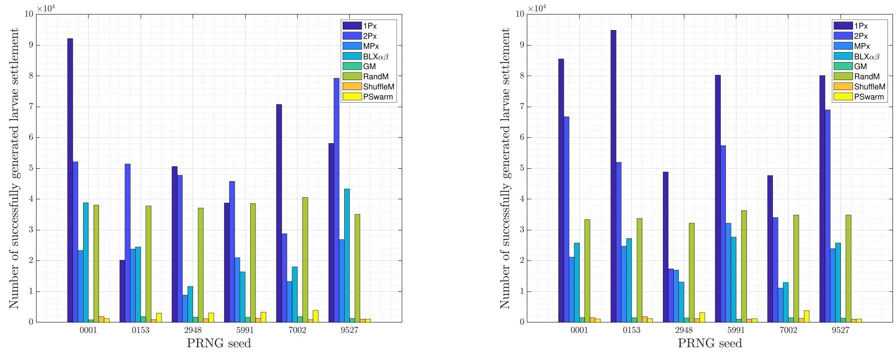
The quality of the initial random-generated population is an important part of the optimization process. This group of

Note: (*):=acidification, ($^\diamond$):=algae, (*$^\diamond$):=acidification + algae.



(a) CRO-SL.

(b) EnvAdapt-CRO-SL ($^\diamond$).



(c) EnvAdapt-CRO-SL (*).

(d) EnvAdapt-CRO-SL (*$^\diamond$).

FIGURE 14. **Substrate layers participation in the larvae settlement process.**

solutions significantly affects the actuation of the different search operators and the performance of the new solutions. The impact analysis on the initialization process has been analyzed following similar procedures to those exposed in [79]. Population initialization tests have been elaborated generating a total of 50 random coral populations of different sizes (25, 50, 75, and 100) using the four PRNGs enumerated in Section V-C2. A comparison of the average result values of the population is shown in Figure 15.

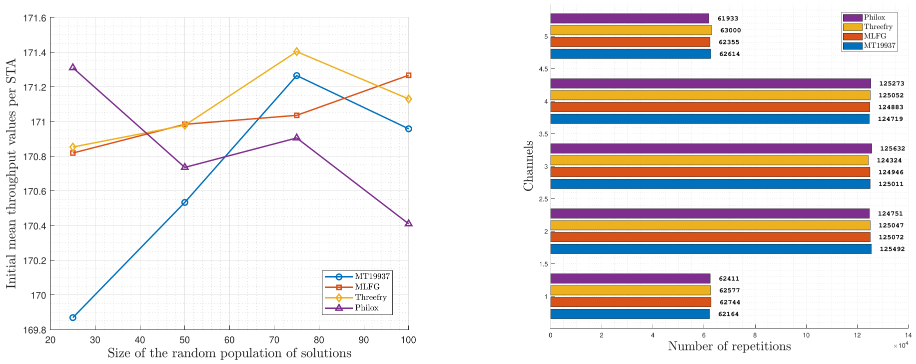
The trends observed in Figure 15a denote that MLFG and Threefry set the most stable initial patterns in creating initial solutions. The Philox generator shows worse initial mean fitness results for a large population of solutions, following a decreasing trend as the population size increases. On the other hand, MT19937 presents the opposite conduct in response to population increments.

A random generation of float real values has been set for the initialization process. Regarding the mean channel distribution for each solution, as it can be seen in Figure 15b and Figure 15d, the selection of channels for each AP shows a similar chance of being chosen. Considering that, for the first case, the values that limit the selected range, $1 \leq x_k \leq 5$, have half the chances of being picked due to the round methodology used to approximate decimal values to integer numbers. In the second case, an equally probable distribution of values has been established, constraining the random values in the range, $0.5 \leq x_k < 5.5$. Better average results for initialization are reached using an equally likely set of values. For that reason, it is recommended to use an equally probable set of values for CAP, resulting in an enhancement of the initial population objective values by approximately 1-2%.

C. INFLUENCE OF PRNGs ON THE OPTIMIZATION PROCESS

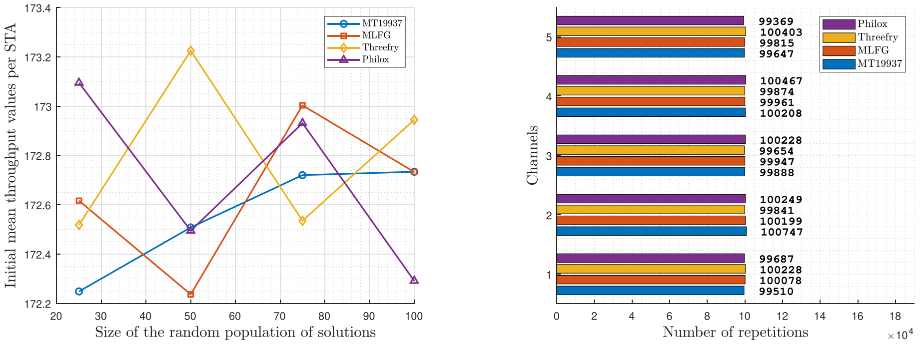
We have measured the impact of PRNGs on the optimization process along the iterations, defining a reef size of 250 holes and an initial population composed of 50 corals. Obtained results are the average values between four test rounds of 30 repetitions for the prior selected PRNGs, along 100 generations.

Figure 16a represents the mean occupation rate of holes by algae. Due to the low initial coral occupation rate of the reef (25%), a high level of algae settlement can be observed for the first generations, with a sharp fall after the decrease of the first generated algae. The stabilization of the algae population has been ongoing since then, gradually occupying approximately 15–20 positions on the reef with each successive generation. A similar average trend is noticed for the four test rounds, regardless of the PRNG used in the optimization process. Observing the fitness evolution



(a) Avg. initial values per STA (non-equally probable).

(b) Non-equally probable distribution of channel values.



(c) Avg. initial values per STA (equally probable).

(d) Equally probable distribution of channel values.

FIGURE 15. **Initial average throughput values per STA generated by different PRNGs.**

represented in Figure 16b, MLFG and Philox denote the best and worst coral population fitness average, respectively, following the trend observed in the prior analysis, in which, MLFG obtained the best average fitness result for large reef sizes whereas the Philox performance declined as the reef size increased.

D. ROBUST OPTIMIZATION PROBLEM WITH STOCHASTIC SCENARIOS

Various techniques can be applied to manage uncertainty and enhance the real-world performance of the optimal solutions obtained through optimization algorithms. In this case, a stochastic scenario generator was developed, following the configuration outlined in Section V-C, to produce nine different scenarios ($N_s = 9$) for a 3-floor building. These scenarios are depicted in Figure 12. A uniform probability density distribution was selected for scenario weighting, assigning equal weight to each scenario for the average fitness computation as

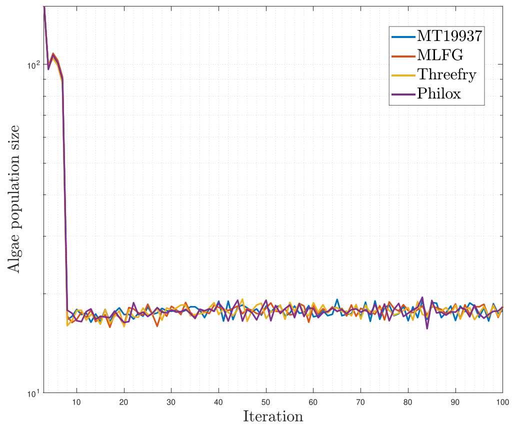
$$F_{\text{avg}} = \sum_{i=1}^{N_s} \omega\, F_i, \quad \text{where } \omega = \frac{1}{N_s}. \tag{16}$$

We also examined the effects of varying the algae colonization hyperparameter. To evaluate the impact of different colonization levels, we fixed the algae rooting probability at five specific values: 0%, 20%, 40%, 60%, and 80%. Additionally, the maximum algae occupation level in the reef was set at 80% of the available holes. The acidification values are influenced by the number of algae present in a given iteration and their relative position on the reef, following the Equation (2) described in Section III-C. The experiment is conducted with an initial population of 125 corals, a reef size of 250 holes, and a stopping criterion of 300 iterations. Each optimization phase is executed 20 times, with Table 3 presenting the average results for each algae rooting probability percentage.

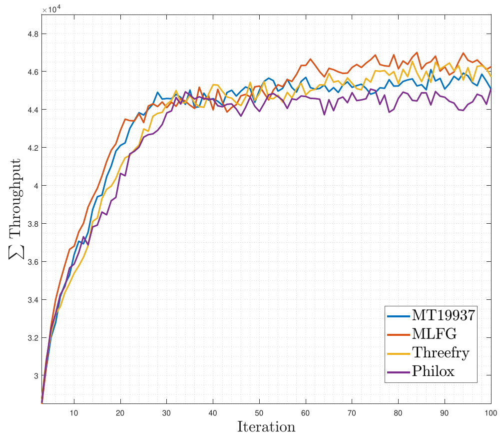
TABLE 3. **Robust optimization average results.**

Prob. of rooting	Avg. $\sum$ throughput (F_{avg})
0%	16726.59
20%	**17182.38**
40%	17093.31
60%	16954.81
80%	16544.09

Regarding the robust optimization results, the highest average fitness values were achieved at lower algae occupation levels, specifically with a 20% algae rooting probability. As shown in Figure 17, higher algae presence on the reef correlates with reduced acidification levels and lower variability in corals. In other words, beyond the 20%



(a) Average size of the algae population.



(b) Average fitness of coral population.

FIGURE 16. **Evolution of mean algae population and corals fitness using different PRNGs.**

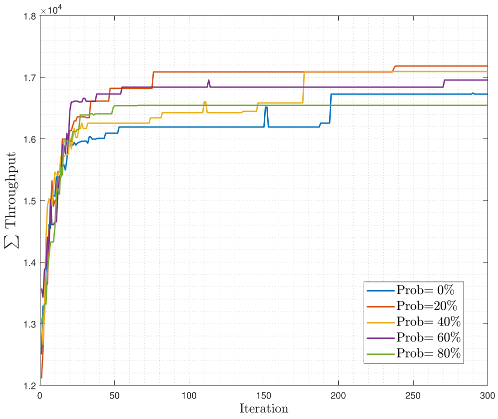


FIGURE 17. **Evolution of robust optimization performance for varying algae rooting probabilities.**

threshold, as the probability of algae taking root increases, fewer corals are generated, reducing the substrate's ability to explore and find optimal solutions, and excessively decreasing the acidification effect on the reef.

VII. CONCLUSION AND FUTURE WORKS

The most common metaheuristics are typically based on simulating isolated behaviors or processes. However, this methodology introduces a new perspective for designing metaheuristic algorithms. It shifts the focus towards modeling entire ecosystems by observing the relationships between different classes of agents. This approach enables the generation of new stochastic procedures aimed at obtaining optimal solutions based on natural interconnected mechanisms between various species and their environments. The proposed environmentally adaptive methods can be applied to expand several bio-inspired algorithms by assembling different agents inside the previously designed frameworks.

Compared to the standard version of the CRO-SL, integrating environmental agents into the EnvAdapt-CRO-SL framework demonstrates slight improvements in the solution quality and the computation time required to obtain them. Higher replacement rates lead to increased population diversity, enhancing the exploration behavior of the substrate layers and enabling them to overcome stagnation states. Additionally, the dynamic and continuous decrease of the fitness threshold facilitates the larvae settlement on the reef, reducing the number of attempts needed to replace existing corals and accelerating the global optimization process. Furthermore, the adaptive behavior of the algorithm reflects the resilience and adaptability observed in natural ecosystems. As the decrease in the standard deviation values indicates, these adaptive features enable the algorithm to adapt dynamically to shifts in the optimization landscape. This fact reduces the impact of the initialization and stochastic processes on the quality of the solutions, ensuring a robust performance across different problem scenarios and environments.

A significant impact of the PRNGs is evidenced in the average fitness of the randomly initialized population and the subsequent evolution of the results across generations. While similar values are obtained for parameters such as algae population or channel number selection, tests show minimal fluctuations between different PRNGs. As proposed in Section III-C, the regulatory mechanisms governing algae colonization demonstrate an effective execution, maintaining the algae population within a defined range.

In future works, the development of new substrates and environmental agents are objectives to address to improve the modeled optimizer. We have written a user's guide [80] seeking to make the access of new users easier without the need to understand the different scripts that compose the framework of the provided EnvAdapt-CRO-SL repository. Additionally, an open-source repository [81] is provided for interested users, allowing the research community and practitioners to contribute to the continued development of the algorithm.

Regarding the wireless network experiments, additional IEEE Wi-Fi standards and interference models can be designed to provide more accurate experiments and the influence of different search landscapes in the performance of the EnvAdapt-CRO-SL algorithms. The generation of dynamic scenarios that incorporate stochastic movement of STAs for finite ranges of time is an interesting case of study for additional tests for new environmentally adaptive algorithms or the implementation of other environmental agents for the EnvAdapt-CRO-SL.

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ANTONIO J. ROMERO-BARRERA received the bachelor's degree in aerospace engineering from King Juan Carlos University (URJC) and the master's degree in AI for the energy and infrastructure sector from UNIR, URJC, and Universidad de Alcalá (UAH), in 2023. Currently, he is pursuing the Ph.D. degree focused on wind energy forecasting and optimization within the IT program of UAH. From 2021 to 2023, he was a Research Assistant with URJC with the FAIaS Erasmus+ project. From 2023 to April 2024, he was a Research Assistant with UAH within the Wi-DAI project. Since then, he has been a Short-Term Quantitative Analyst with the Short-Term Trading and Strategy Department of Axpo Iberia SL. His bachelor's thesis won the National Award for works related to Energy Transition, in 2022 and 2023, academic year from the University of Santiago de Compostela (USC) and Genesal Energy. His bachelor's and master's theses also received first prize for works related to the SDGs from URJC, in 2023.

LUIS CRUZ-PIRIS received the Telematics Engineering degree in telecommunication engineering, and the master's and Ph.D. degrees from the University of Alcala (UAH), in 2012, 2016, and 2019, respectively. Since 2020, he has been an Assistant Professor of telematics engineering with UAH. He has worked on multiple research projects on multimodal transportation systems, simulation, and cybersecurity. His research interests include intelligent agents, wireless networks, the IoT architectures, and intelligent transportation systems.

MARINO TEJEDOR-ROMERO received the bachelor's degree in telematics engineering, the master's degree in cybersecurity, and the Ph.D. degree (cum laude) in sciences from the Universidad de Alcalá, Spain, in 2015, 2019, and 2023, respectively. He has been involved in the teaching of undergraduate courses in telecommunications and computer science with the Universidad de Alcalá. His research interests vary from wireless networks and electronic voting to graphs and geometry applied to opinion analysis. Additionally, he is focused on powering teaching and research with new generation resources, such as interactive educative material on the web, advanced animations, and integrated notebooks.

JOSE MANUEL GIMENEZ-GUZMAN received the M.S. and Ph.D. degrees (cum laude) in telecommunication engineering from Universitat Politècnica de València, Spain, in 2002 and 2008, respectively. From 2008 to 2021, he was an Associate Professor with the University of Alcala, Spain. He has been a Visiting Scholar with the University of Wurzburg, Germany, in 2012, and Aalborg University, Denmark, in 2023. He is currently an Associate Professor with Universitat Politècnica de València, where he is engaged in research and teaching in the areas of analysis and performance evaluation of wireless networks and optimization of complex networked systems. He has published more than 60 technical papers in these areas in international journals and conference proceedings. He is an Associate Editor of *Wireless Networks* journal.

IVAN MARSA-MAESTRE received the degree in telecommunication engineering and the Ph.D. degree from Universidad de Alcalá, Spain, in 2003 and 2009, respectively. He is currently a Full Professor with the Computer Engineering Department, Universidad de Alcalá. His research interests include the use of negotiation and nonlinear optimization techniques for distributed coordination of complex systems, such as computer networks, supply chains, and vehicle management systems. He has taken part in many public and private research projects in these matters, has a number of publications in high-impact international conferences and journals, and serves as a guest editor, the program chair, and a reviewer for some of them. From his research have emerged collaborative research lines with international research groups, such as the Center for Green Computing, Nagoya Institute of Technology in Japan, the Technical University of Delft (TUDelft) and the Center for Collective Intelligence, and Massachusetts Institute of Technology in USA.

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