

Emerging Trends in Multi-Agent Systems from an Evolutionary Perspective

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Abstract

Nature provides great examples of Multi-Agent Systems (MASs), in which two or more agents may interact with each other. The nature of such interactions might vary from a predator-prey relationship to collective behaviors up to independent agents (i.e., absence of interactions). Among these examples, collaboration represents a worthwhile topic, since it involves delving into the mechanisms determining social behaviors in animals, like ants, birds and fish, and in humans. With respect to evolutionary theory, a conventional approach is to leverage the full potential of Evolutionary Algorithms (EAs), i.e. bio-inspired optimization metaheuristics that proved to be viable and effective tools in a broad range of domains. Thanks to their versatility, EAs lay down the foundation for the discovery of optimized MASs, and prior studies emphasize the efficacy of these methods in cooperative scenarios like aggregation and foraging. This research investigates the ability of two recently introduced EAs — Population OpenAI-ES (PopOpenAI-ES) and Stochastic Steady State with Hill-Climbing (SSSHC) — to evolve solutions with regard to two cooperative MAS problems. For each task, we examined two evolutionary conditions: (i) the evolution of a homogeneous MAS (i.e., “homogeneity”), and (ii) the evolution of a heterogeneous MAS formed by individuals evaluated in homogeneous MASs (i.e., “mixed homogeneity-heterogeneity”). Therefore, our study proposes a novel framework to discover effective heterogeneous MASs through an evolutionary search driven by the usage of homogeneous MASs. The analysis unveils that SSSHC outperforms PopOpenAI-ES in both scenarios and for both conditions, hence underscoring the importance of rethinking the way in which EAs are designed and using tailored methods based on the application domain. Moreover, the proposed framework enables the discovery of successful heterogeneous MASs, especially with SSSHC.

Keywords

Multi-Agent Systems, Evolutionary Algorithms, PopOpenAI-ES, SSSHC, Homogeneity, Heterogeneity

1. Introduction

Nature provides manifold examples of astonishing creatures co-living with others and, sometimes, interacting in different manners. In particular, animal species like ants, birds, cockroaches, fish or sheep represent extraordinary examples of Multi-Agent Systems (MASs) [1, 2]. By definition, a MAS is a system formed by multiple interacting agents, which can solve problems that are challenging for a single agent [1]. We can also think MASs as systems formed by two or more agents that could either collaborate, or compete, or ignore each other [3]. Agents in a MAS may be Large Language Models (LLMs) [4], robots [5], sensors [6, 7] or software agents [8, 9].

By looking at natural organisms exhibiting cooperative strategies inspiring MASs, ants exploit pheromone-based communication to effectively forage [10, 11]. Bees use sophisticated techniques like thermo-regulatory behaviors [12] or dancing patterns [13] to interact and communicate. Flocking in birds increase the survival chance of individuals [14, 15]. One of the greatest and widespread examples of collective behavior in animal species is aggregation [16], particularly in social animals such as ants [17–19], bees [20, 21], birds [22, 23], cockroaches [24, 25], fish [26, 27] and worms [28, 29].

These examples laid the foundation for the development of swarm robotics [30, 31], i.e. a subfield of MASs in which agents cooperate with the aim to achieve a collective outcome that goes beyond their individual capabilities. Generally, applications of swarm robotics make the assumption about the agents’ homogeneity (i.e., sharing the same body and brain). Nonetheless, heterogeneous MASs might ease the solution of problems through task-specialization and division of labor mechanisms [32, 33].

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Moreover, examples in nature prove that heterogeneity might be beneficial for the development of collective behaviors [34, 35].

One pioneering approach to identify viable solutions for MASs involves the usage of Evolutionary Algorithms (EAs) [36], i.e. optimization metaheuristics with a broad spectrum of applications [37]. Because these algorithms are biologically inspired by theory of evolution in natural organisms, EAs emerged as a promising approach to both model this phenomenon and solve different scenarios. Nonetheless, over the last two decades, there has been a clear paradigm shift toward the second aim, and researchers mainly focused on performance enhancement. This has led to a variety of EAs proposed in literature, some of which represent viable approaches to tackle MAS problems [38, 39].

This research compares two recently proposed EAs — Population OpenAI Evolutionary Strategy (PopOpenAI-ES) [40] and Stochastic Steady State with Hill-Climbing (SSSHC) [41, 42] — for their capability of evolving effective behaviors in MASs. The former is a population variant of the OpenAI Evolutionary Strategy (OpenAI-ES) [43], which represents one of the most advanced and effective EAs in literature [44]. Conversely, the latter is a population algorithm combining SSS and the Hill-Climbing (HC) algorithm [45]. We select these two algorithms since they proved superior to OpenAI-ES in a recent study on 50 different problems [40]. Specifically, we investigate two benchmark problems for MASs: foraging with poison [46, 47] and swarm aggregation [39, 48, 49]. Furthermore, we analyze the performance difference under two experimental conditions:

- **homogeneity:** the algorithms must discover solutions for a MAS formed by homogeneous agents sharing the same neural network controller. This criterion drives the search throughout the whole evolutionary process;
- **mixed homogeneity-heterogeneity:** the algorithms must discover solutions for a MAS formed by heterogeneous agents, i.e. controlled by different neural networks. However, the search for solutions is driven by the evaluation of homogeneous MASs, and the evaluation of the heterogeneous MAS is done by considering the evolving population (see Fig. 1).

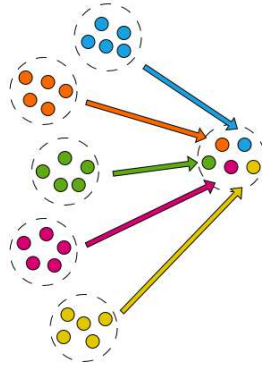


Figure 1: Evolution of a heterogeneous MAS from homogeneous ones.

The goal of our research is threefold:

1. investigating the effectiveness of modern EAs with respect to MASs;
2. proposing a novel evolutionary framework to enable the discovery of successful heterogeneous MASs by driving the search through the evaluation of homogeneous MASs;
3. capturing possible relationships between algorithm features and performance.

Our findings highlight the superiority of SSSHC over PopOpenAI-ES with respect to both problems and both conditions. Furthermore, the performance is higher in the homogeneity condition than in the mixed homogeneity-heterogeneity condition regardless of the algorithm used. Surprisingly, the effectiveness of the heterogeneous MAS discovered by SSSHC bests the results obtained by PopOpenAI-ES in the homogeneity condition. The latter outcome suggests that SSSHC represents a better option for the discovery of successful heterogeneous MASs in our scenario.

2. Related Works

As we stated in Section 1, MAS and swarm robotics research fields involve analyzing groups of agents cooperating to cope with problems that are too complex (or not feasible) for a single agent, with the aim to study how biological animal societies behave and self-organize. Modeling and attempting to reproduce and explain collective behaviors observed in nature lead to a broad literature in the field, especially regarding aggregation [39, 50–54], collective transport [55–59], coverage [60–64] and foraging [32, 38, 46, 60]. A widespread assumption in swarm robotics (and in robotic MASs) is the agents’ homogeneity, i.e. they share the same physical embodiment and brain. The main advantage is to narrow the search in the solution space. Nevertheless, heterogeneous MASs represent a great opportunity to deal with complex task by leveraging physical and behavioral differences between agents, which might specialize and/or address diverse sub-goals [32, 33]. For example, the study in [33] shows that heterogeneity promotes effective task specialization in a robotic MAS aiming to solve a perception task. In [65], the authors demonstrate that heterogeneous MASs outperform homogeneous MASs in an aggregation scenario inspired by juvenile honeybees.

Among the approaches used in MAS and swarm robotics scenarios, Evolutionary Algorithms (EAs) emerged as an effective and widespread technique. In [54], the Generational Genetic Algorithm (GGA) [66] is used to evolve an aggregation behavior in robotic MASs formed by N simulated s-bots [67, 68] (with $N \in [5, 10, 20]$). In [56], a successful collective transport problem by a robotic MAS formed of N simulated s-bots (with $N \in [4, 8, 12, 16]$) is evolved with a $(\mu + \lambda)$ Evolutionary Strategy (ES) [69, 70]. The use of the EvoStick EA [71] to solve a cooperative aggregation task in a MAS of both simulated and real E-puck robots [72] is presented in [71, 73]. The authors in [38] compare different EAs — Covariance Matrix Adaptation Evolutionary Strategy (CMA-ES) [74], NeuroEvolution of Augmenting Topologies (NEAT) [75], Separable Natural Evolution Strategies (sNES) [76, 77], Stochastic Steady State (SSS) [78] and Exponential Natural Evolution Strategies (xNES) [77, 79] — for the ability to solve a collective foraging problem in a MAS formed by 10 simulated MarXbot [80] robots. Q-learning [81] is used to evolve cooperation in a MAS [82]. GGA has also been employed to analyze social dynamics in two-agent systems [83–85]. Recent studies pointed out that the relationship between Evolutionary Computation (EC) and MASs opens new perspectives on the advantages that both approaches might gain from each other [86], ultimately leading to the emergence of frameworks like Evolutionary Multi-Agent Systems (EMAS) [87].

Because EAs showed versatility and effectiveness in a wide range of domains, researchers started focusing on the development of novel EAs and/or the discovery of mechanisms enhancing their performance. For example, the OpenAI Evolutionary Strategy (OpenAI-ES) [43] recently established as a generally effective EA [44, 88, 89] with applications in robot locomotion [40, 44, 90–92], swarm robotics [3, 39, 48, 89, 93], classic control [44, 89, 94], Atari games [43, 95], Deep Learning (DL) [96], competitive co-evolution [89, 97], parity problems [40], test function optimization [40] and Multi-Objective Optimization (MOO) [94]. However, recent works showed that OpenAI-ES is outperformed by relatively simple methods like SSSHC, hence emphasizing that complexity does not necessarily translate into efficiency [40, 94]. Furthermore, population variants such as PopOpenAI-ES might be more suitable for MAS scenarios.

Overall, the landscape of EAs applied to MAS scenarios is rich in methods, but practical guidelines to choose one algorithm over another have yet to be provided. In this respect, the work in [47] suggests some criteria to be taken into account, based on a preliminary investigation in MAS foraging problems.

3. Materials and Methods

This section provides an overview of the two problems, the evolutionary algorithms, the conditions and the parameters used.

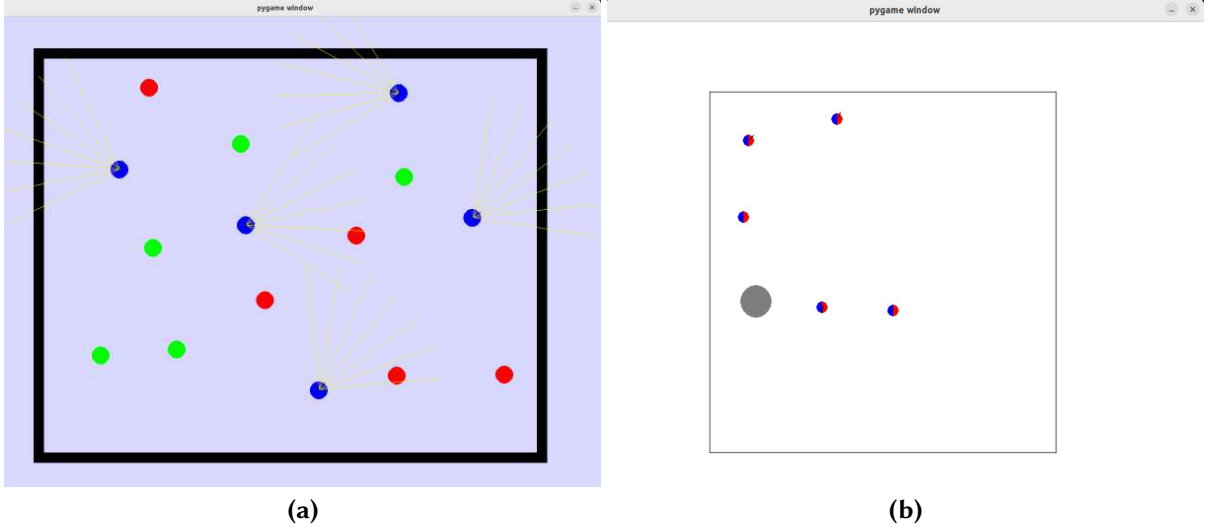


Figure 2: Evolutionary problems. (a) Foraging with poison: a MAS of 5 robots (shown in blue) must seek to forage as many food items (shown in green) as possible, while avoiding poison items (shown in red). (b) Swarm aggregation: a MAS of 5 robots (shown in red and blue) must aggregate in the environment, and a nest (shown in gray) is a possible target for the aggregation.

3.1. Foraging with poison

The first problem is the foraging with poison task [46, 47], which represents a particular case of the general foraging problem involving both individual agents [98, 99] and MASs [38, 44]. The problem is illustrated in Fig. 2-(a): a group of 5 robotic agents (blue circles) must cooperate with the aim to forage as many food items (green circles) as possible, while avoiding poisonous items (red circles). The environment is a rectangular arena of size 10×8 meters surrounded by walls, which contains 5 food items and 5 poisonous items. The performance of the MAS is measured according to the fitness function defined in Eq. 1.

$$F_f = \frac{1}{N_E} \sum_{e=1}^{N_E} (N_f - N_p) \quad (1)$$

In Eq. 1, N_f is the number of foraged food items at the episode e , N_p is the number of poisonous items eaten by the MAS at the episode e , and N_E is the number of episodes. The fitness function F_f is thus bounded in the range $[-5.0, 5.0]$.

Each agent is equipped with a linear camera allowing it to detect colored objects and other agents within 2.5 meters, with a field of view of 90° .

3.2. Swarm aggregation

The second problem is the swarm aggregation task [39, 48, 49], which is shown in Fig. 2-(b): a MAS of 5 robots (blue/red circles) must aggregate in a square 5×5 m arena. A nest (gray circle) represents a possible aggregation area giving a bonus to the MAS. The performance of the MAS is defined according to Eqs. 2 - 3.

$$F_a = \frac{1}{N_E} \sum_{e=1}^{N_E} \sum_{r=1}^{N_R} f_r \quad (2)$$

$$f_r = B_{nest}(r) + k_{dist} \times \left(1 - \frac{1}{N_R - 1} \sum_{o=1}^{N_R-1} \frac{d_{ro}}{d_{MAX}}\right) \quad (3)$$

In Eq. 3, $B_{nest}(r)$ denotes the bonus (set to 1.0) given to the agent r if it reaches the nest, while the term $k_{dist} \times (1 - \frac{1}{N_R-1} \sum_{o=1}^{N_R-1} \frac{d_{ro}}{d_{MAX}})$ rewards the agent r when its average distance from the others is low. Specifically, d_{ro} is the distance between agents r and o , d_{MAX} is the maximum distance set to the diagonal of the arena, N_R represents the number of agents (with $N_R = 5$), and k_{dist} is a coefficient set to 1.0.

Each agent is endowed with a linear camera consisting of 4 45° sectors that enable the detection of red/blue pixels, 32 infrared sensors grouped in 8 blocks of 4 adjacent units allowing to perform wall-detection and 2 ground sensors to perceive the nest.

3.3. Algorithms

Our research focuses on two recently proposed EAs. The first algorithm is PopOpenAI-ES [40], a population variant of OpenAI-ES that demonstrated good performance on 50 different problems [40]. Differently from OpenAI-ES, PopOpenAI-ES evolves a population of μ independent individuals called “centroids”, and stores μ pairs of momentum vectors collecting historical performance information, which are used to identify promising regions of the search space. A key advantage of PopOpenAI-ES over OpenAI-ES is the reduced probability to get stuck in sub-optimal solutions, which is crucial in combinatorial problems [40]. However, evolving a population of centroids requires additional time, with no guarantee of performance enhancements. Differently from the original formulation proposed in [40], we do not enable the replacement of the worst centroids.

The second algorithm is the Stochastic Steady State with Hill-Climbing (SSSHC) algorithm [42], which combines SSS and HC: the former guides the exploration in the solution space and attempts to improve solutions through mutations, whereas the latter performs a local refinement through single-gene modifications [41]. This mechanism allows the algorithm to balance exploration and exploitation. As demonstrated in [40, 94], in spite of its simplicity, SSSHC outperforms or is competitive with OpenAI-ES with regard to a broad spectrum of problems.

3.4. Homogeneity vs mixed Homogeneity-Heterogeneity

As anticipated in section 1, two evolutionary conditions have been used. In a first series of experiments, PopOpenAI-ES and SSSHC seek to evolve effective solutions for a homogeneous MAS, a condition called “homogeneity”. With this term we mean a group with a shared neural network controller: the architecture and parameters of the network are the same for each agent, but the positions of the agents vary and so do the agents’ behaviors. This is a common approach when using EAs in MAS scenarios [38, 54]. Specifically, the evaluation of homogeneous MASs drives the search for solutions throughout the whole evolutionary process. Conversely, in a second series of experiments, PopOpenAI-ES and SSSHC are evaluated in the so-called “mixed homogeneity-heterogeneity” condition: the aim is to discover effective solutions for a heterogeneous MAS, i.e. a group in which each agent is controlled by a different neural network (only parameters differ, the architecture of the network is the same), but the search in the solution space is driven by the evaluation of homogeneous MASs. At each iteration of the algorithms, the evolving population is used to create a heterogeneous MAS (see Fig. 1), which is evaluated. The key idea is to reduce the time required to evolve a heterogeneous MAS from scratch or through sophisticated techniques like N-mates [100, 101]. Nonetheless, there is no guarantee that the approach works, since the creation of a heterogeneous MAS from solutions discovered for a homogeneous MAS might have disruptive effects. In fact, as pointed out in [100], the effectiveness of a heterogeneous MAS depends primarily on each agent’s skills.

3.5. Parameters

Most of the parameters have been inherited from previous studies [39, 40, 48, 49]. In particular, Table 1 reports the algorithmic parameters used, Table 2 illustrates the experimental settings and Table 3 contains a description of the neural network controllers. Specifically, we set the population size μ to 5 for both algorithms, since the considered MASs are formed by 5 agents. This is particularly relevant

in the mixed homogeneity-heterogeneity condition, in which we use the whole population to create a heterogeneous MAS. To ensure a fair comparison, the mutation rate σ has been set to 0.02, which represents a value commonly adopted for OpenAI-ES [39, 44].

Table 1

Algorithms' parameters. The symbol “-” is used when a parameter is meaningless for the corresponding algorithm (e.g., the number of samples λ is not defined for SSSHC).

	PopOpenAI-ES	SSSHC
PopSize (μ)	5	5
MutRate (σ)	0.02	0.02
# of samples (λ)	20	-
# of refinement iterations (k)	-	5

Concerning the experimental settings reported in Table 2 and the neural network parameters in Table 3, the parameter values correspond to those defined in [39, 40]. This enables a fair comparison with existing studies. The number of replications N_{rep} has been set to 20 in order to exclude biases in the outcomes.

Table 2

Experimental settings. The parameter values have been inherited from existing studies [39, 40] for replicability and compatibility purposes.

	Foraging with poison	Swarm aggregation
# of replications (N_{rep})	20	20
# of evaluation steps (N_{eval})	5×10^7	1.5×10^9
# of robots (N_R)	5	5
# of episodes (N_E)	5	20
# of episode steps (N_{step})	1000	1000

Table 3

Network parameters. Inputs: 26 for the foraging with poison problem (18 inputs from 6 channels of the RGB camera + 8 inputs from IR sensor); 14 for the swarm aggregation problem (8 infrared sensors + 4 camera sensors + 2 ground sensors). The values are derived from [39, 40].

	Foraging with poison	Swarm aggregation
Type	Feed-forward	Recurrent [102, 103]
# of inputs (N_I)	26	14
# of hidden neurons (N_H)	50	10
# of outputs (N_O)	2	4
Activation function	Tanh	Tanh
Bias	Yes	Yes
Weight range (w)	$[-1.0, 1.0]$	$[-1.0, 1.0]$

The experiments have been performed with evorobotpy3 [88], a simulation engine widely adopted to experiment with EAs and MASs [3, 89, 94].

4. Results

To ease the readability, we adopted the following formulation: regarding the evolution of homogeneous MASs, we termed PopOpenAI-ES as “Alg1” and SSSHC as “Alg2”, respectively. Similarly, the terms “Alg1m” and “Alg2m” refer to the evolution of MASs in the mixed homogeneity-heterogeneity condition by means of PopOpenAI-ES and SSSHC, respectively. All the outcomes are shown by considering the normalized fitness, i.e. we kept the fitness bound in the range $[0.0, 1.0]$. In order to verify significant differences among the methods, we employed the Mann-Whitney U statistical test and we applied the post-hoc Bonferroni correction.

The performance analysis at the end of evolution underscores notable differences: as illustrated in Table 4, Fig. 3 and Fig. 4, Alg2 and Alg2m significantly outperform Alg1 and Alg1m with respect to both problems (see Table 4). As regards the foraging with poison problem, Alg2 and Alg2m manage to optimally solve the task (see Table 4 and Fig. 3), while their performance is slightly below optimality in the swarm aggregation problem. Interestingly, Alg2 and Alg2m perform similarly in both domains ($p > 0.05$, see Fig. 4). This implies that the mixed homogeneity-heterogeneity condition affects Alg2 only partially. Instead, it causes a significant drop in the performance of Alg1 (see Table 4 and Fig. 3). This is related to the operation of the algorithm: because the momentum vectors direct exploration in the solution space through historical information, the utilization of homogeneous MAS results in a sub-optimal search. Conversely, Alg2 relies only on simple mutation operators, which are less sensitive to such issues.

Table 4

Normalized fitness (mean $\pm$ standard deviation). Best performance is presented in bold. Data are averaged over 20 replications.

	Foraging with poison	Swarm aggregation
Alg1	0.906 ± 0.067	0.686 ± 0.044
Alg2	1.0 ± 0.0	0.889 ± 0.080
Alg1m	0.740 ± 0.077	0.582 ± 0.024
Alg2m	1.0 ± 0.0	0.874 ± 0.081

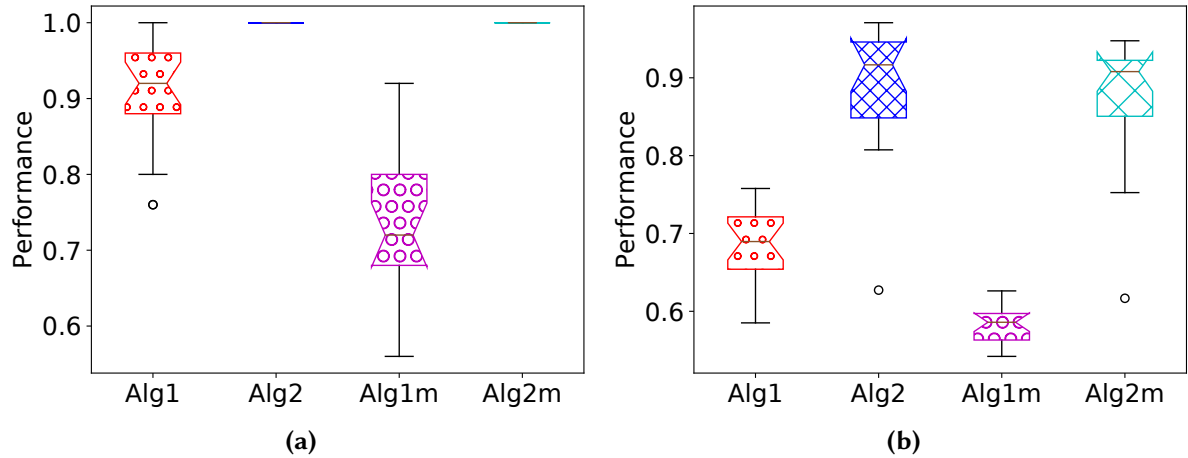


Figure 3: Fitness at the end of evolution. Data are averaged over 20 replications. (a) Foraging with poison. (b) Swarm aggregation.

As shown in Fig. 5, Alg2 and Alg2m rapidly improve performance in the early stages of evolution (Fig. 5, blue and light-blue curves): they quickly converge to the optimal solution with respect to the foraging with poison problem (see Fig. 5-(a)), and reach a good performance level in the first half of the evolutionary process with regard to the swarm aggregation problem (see Fig. 5-(b)). On the other hand, Alg1 and Alg1m exhibit a slower enhancement (Fig. 5, red and purple curves). This finding aligns with previous studies indicating that Alg1 needs a boost phase before actually improving performance [44, 94]. Moreover, the performance of Alg1 and Alg1m has not yet converged at the end of the evolutionary process with respect to the foraging with poison problem (see Fig. 5-(a)). Concerning the swarm aggregation problem, all the considered algorithms show trends towards a performance enhancement at the end of evolution (see Fig. 5-(b)).

Because the fitness function achieved during evolution is affected by the randomness of the initial conditions, we assess the effectiveness of the evolved solutions through a post-evaluation test on fixed 50 episodes, which represents a common approach in literature [38, 78]. The results of the post-evaluation test are shown in Table 5, Fig. 6 and Fig. 7 and confirm the superiority of Alg1 and Alg1m over Alg2 and

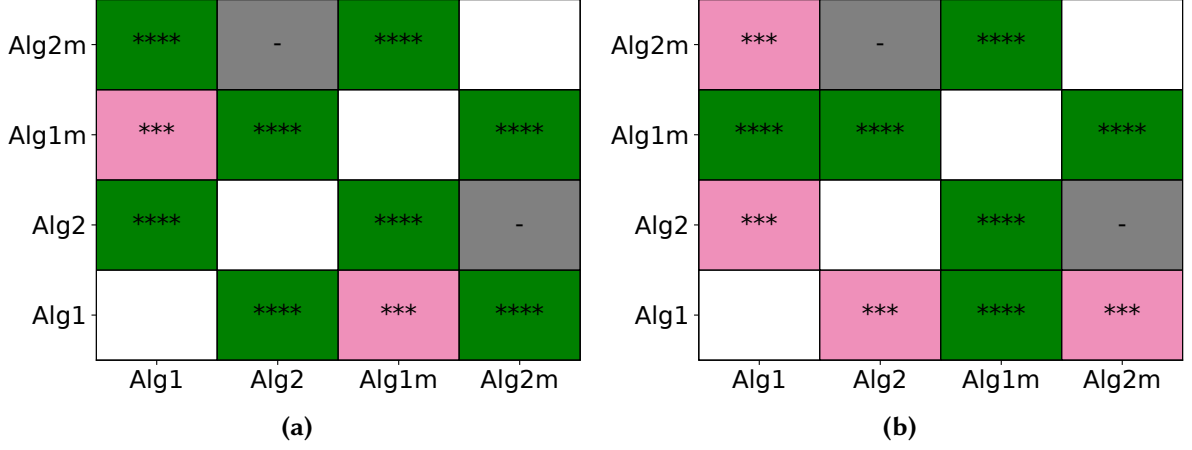


Figure 4: Statistical comparison of the different algorithms. Symbols are defined as follows: “-”: not significant; “*”: significant at $p < 0.05$; “**”: significant at $p < 0.01$; “***”: significant at $p < 0.001$; “****”: significant at $p < 10^{-6}$. Data are averaged over 20 replications. (a) Foraging with poison. (b) Swarm aggregation.

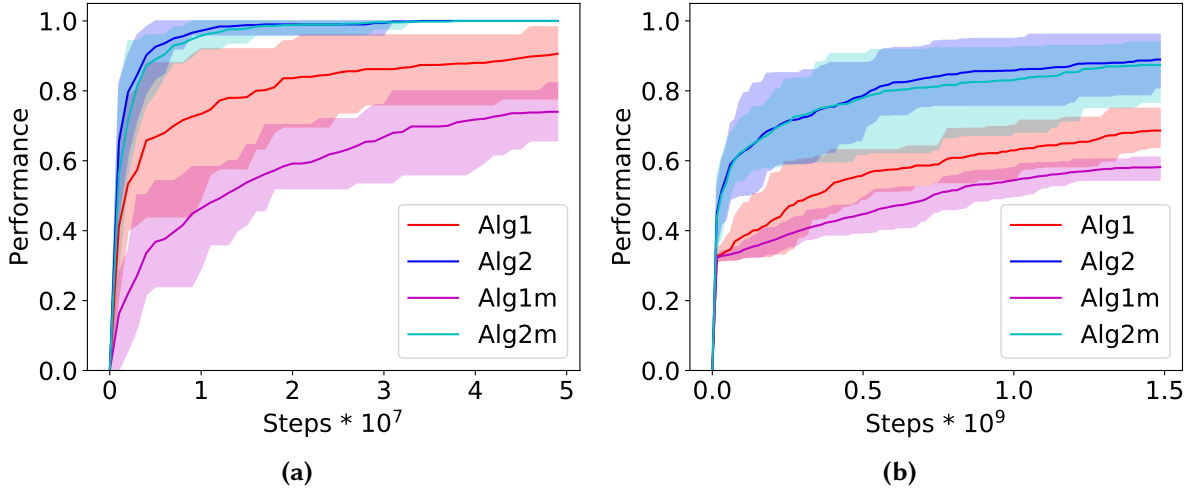


Figure 5: Fitness curves during evolution. Data are averaged over 20 replications. (a) Foraging with poison. (b) Swarm aggregation.

Alg2m. Unexpectedly, the algorithm performance decreases in both tasks, although the drop is more pronounced for the foraging with poison problem. This is mainly due to the difference in the value of N_E (see Table 2): evaluating MASs on a limited number of episodes do not ensure generalization capabilities, since the outcomes might be biased by lucky environmental conditions. Conversely, exposing MASs on a broader set of episodes (as for the swarm aggregation problem) fosters robustness to environmental perturbations and generalization. Overall, we observe a general reduction in the statistical differences between the algorithms (see Fig. 7).

Table 5

Normalized fitness (mean $\pm$ standard deviation) during post-evaluation test. Best performance is presented in bold.

	Foraging with poison	Swarm aggregation
Alg1	0.708 $\pm$ 0.082	0.651 $\pm$ 0.038
Alg2	0.821 $\pm$ 0.049	0.795 $\pm$ 0.090
Alg1m	0.505 $\pm$ 0.263	0.568 $\pm$ 0.062
Alg2m	0.788 $\pm$ 0.068	0.772 $\pm$ 0.100

Our outcomes emphasize that the evolution of a heterogeneous MAS driven by the usage of homo-

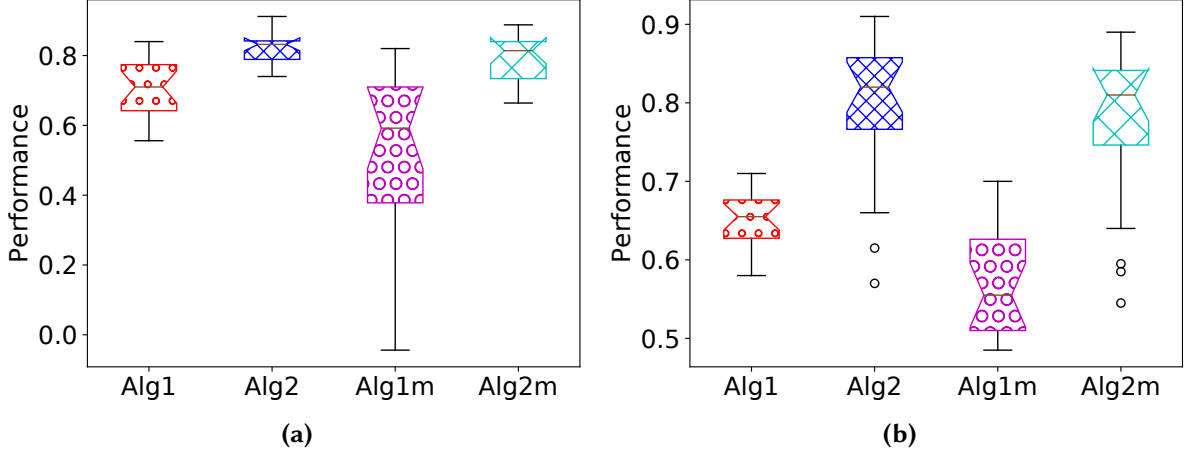


Figure 6: Fitness obtained during post-evaluation test. Data are averaged over 20 replications. (a) Foraging with poison. (b) Swarm aggregation.

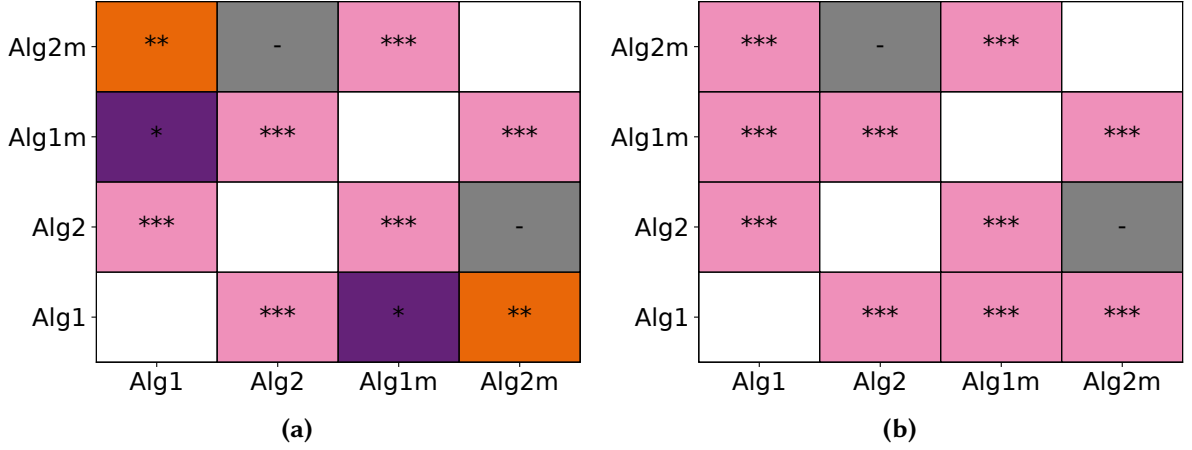


Figure 7: Statistical comparison of the different algorithms during post-evaluation test. Symbols are defined as follows: “-”: not significant; “*”: significant at $p < 0.05$; “**”: significant at $p < 0.01$; “***”: significant at $p < 0.001$; “****”: significant at $p < 10^{-6}$. Data are averaged over 20 replications. (a) Foraging with poison. (b) Swarm aggregation.

geneous MASs (i.e., the mixed homogeneity-heterogeneity condition) represents a viable framework for the discovery of effective heterogeneous groups, in which each agent has its own skills, provided that we select the appropriate EA. In fact, SSSHC proves more suitable than PopOpenAI-ES, since its underlying mechanism relies on mutation operators, which work independently of the evolutionary drive (homogeneity vs mixed homogeneity-heterogeneity). On the other hand, PopOpenAI-ES is highly sensitive to the specific condition, because it exploits historical performance information to channel the search in the solution space. This results in a sub-optimal evolutionary search in the mixed homogeneity-heterogeneity condition, where the creation of a heterogeneous MAS is achieved by selecting neural network controllers evaluated in homogeneous MASs.

Another factor determining the superiority of SSSHC over PopOpenAI-ES relies on the size of neural network weights, especially with respect to the swarm aggregation problem (see Table 6 and Fig. 8): the absolute value $|w|$ of the neural network weights evolved by SSSHC is 2.5 times higher than the value discovered by PopOpenAI-ES. This result is not surprising, since OpenAI-ES, and therefore PopOpenAI-ES, has an intrinsic tendency to narrow the weights to small values [39, 44]. While this feature is beneficial in robot locomotion problems [44], it does not necessarily extend to all scenarios [40]. Concerning the foraging with poison problem, PopOpenAI-ES and SSSHC evolve controllers characterized by $|w| \approx 0.5$.

Table 6

Absolute value of neural network weights $|w|$ (mean $\pm$ standard deviation) of the best evolved MASs. For Alg1m and Alg2m, the data are averaged over the μ agents forming the heterogeneous MAS.

	Foraging with poison	Swarm aggregation
Alg1	0.477 ± 0.007	0.193 ± 0.032
Alg2	0.489 ± 0.008	0.499 ± 0.017
Alg1m	0.467 ± 0.004	0.183 ± 0.008
Alg2m	0.492 ± 0.008	0.500 ± 0.018

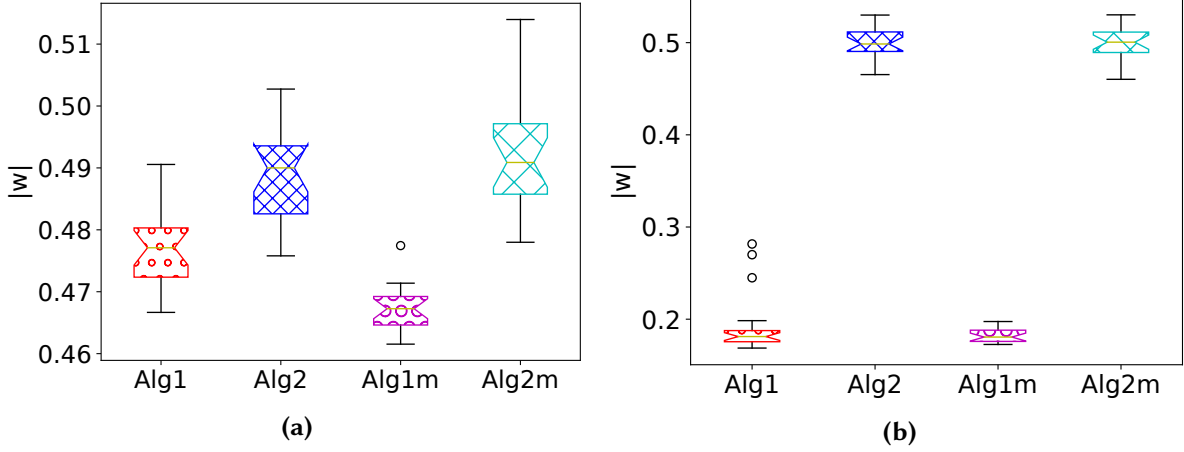


Figure 8: Absolute value of neural network weights $|w|$. Data are averaged over 20 replications. (a) Foraging with poison. (b) Swarm aggregation.

Overall, in the considered scenario, our analysis underscores that SSSHC represents a better option for the discovery of both homogeneous and heterogeneous MASs than PopOpenAI-ES. Furthermore, the proposed framework enables to evolve effective heterogeneous MASs even when evolution is driven by the evaluation of homogeneous MASs. Lastly, our investigation puts emphasis on the need to rethink the way in which EAs are designed: the usage of mechanisms like historical information preservation or weight minimization are not always effective, and their efficacy is related to the properties of the considered scenario. As a consequence, using simple EAs might result in enhanced performance and robustness against domain-specific pitfalls [104].

5. Conclusions

The framework of Multi-Agent Systems (MASs) was born with the aim to tackle complex problems that are beyond the capabilities of individual agents. Despite the broad nature of agents (e.g., robots, software agents), the theoretical foundation of the MAS framework comes from observing animal species (ants, birds or fish) behaving and acting as a whole system. These organisms exhibit complex and sophisticated patterns at a system level from basic capabilities at the individual level, and can solve relatively difficult problems. Despite the vast literature in the field of MASs, modeling and replicating the dynamics of social animals through empirical evidence still present challenges. A straightforward approach to discover possible solutions for MASs exploits Evolutionary Algorithms (EAs), which are optimization metaheuristics largely adopted in Evolutionary Computation (EC). A common assumption is to consider homogeneous MASs, i.e. systems in which agents are identical with respect to both physical embodiment and brain. Although this design choice narrows the search space, it also limits the types and behavioral strategies discovered. Moreover, heterogeneous MASs might leverage individual differences to foster behavioral diversity and specialization.

Another shortcoming is related to the explosion of EAs over the last two decades, with a notable shift from biological inspiration to performance optimization. In this respect, although these methods offer

viable alternatives in many domains, practitioners do not always know which algorithm is more suitable for a specific scenario. Moreover, the complexity of recently introduced EAs does not always correspond to enhanced performance, especially when the problem features interfere with the algorithm’s operation.

This research delves into the analysis of two recently proposed EAs, called PopOpenAI-ES and SSSHC, for the discovery of effective MASs. Specifically, two benchmark problems — foraging with poison and swarm aggregation — and two conditions — homogeneity and mixed homogeneity-heterogeneity — have been considered. On one side, we aimed to investigate the effectiveness of modern EAs in discovering successful MASs. On the other side, we formulated a novel framework to discover heterogeneous MASs by mixing agents that have been evaluated in homogeneous MASs.

The main findings of this research might be summarized as follows:

- a novel framework for the discovery of heterogeneous MASs is proposed, in which the evolutionary search is driven by the analysis of homogeneous MASs;
- SSSHC outperforms PopOpenAI-ES with respect to both problems;
- SSSHC is superior to PopOpenAI-ES in both homogeneity and mixed homogeneity-heterogeneity conditions;
- the evaluation of homogeneous MASs as evolutionary drive in the mixed homogeneity-heterogeneity affects PopOpenAI-ES and explains its sub-optimality;
- complexity does not necessarily translate into enhanced performance, but is tightly related to the experimental setup.

The presented study focuses the investigation on two recently proposed EAs, which demonstrated state-of-the-art performance in several benchmark problems but are not specifically tailored for MASs. Therefore, a straightforward future research direction might be the analysis of methods designed for MASs, such as Particle Swarm Optimization (PSO) [105] or Ant Colony Optimization (ACO) [106], or simple EAs like GGA. Another future avenue might consider extending our framework to complex MAS domains like collective robot locomotion [107] or task allocation [108].

Table of acronyms

ACO	Ant Colony Optimization
CMA-ES	Covariance Matrix Adaptation Evolutionary Strategy
DL	Deep Learning
EA	Evolutionary Algorithm
EC	Evolutionary Computation
EMAS	Evolutionary Multi-Agent Systems
ES	Evolutionary Strategy
GGA	Generational Genetic Algorithm
HC	Hill-Climbing
LLM	Large Language Model
MAS	Multi-Agent System
MOO	Multi-Objective Optimization
NEAT	NeuroEvolution of Augmenting Topologies
OpenAI-ES	OpenAI Evolutionary Strategy
PopOpenAI-ES	Population OpenAI Evolutionary Strategy
PSO	Particle Swarm Optimization
sNES	Separable Natural Evolution Strategies
SSS	Stochastic Steady State
SSSHC	Stochastic Steady State with Hill-Climbing
xNES	Exponential Natural Evolution Strategies

Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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