Multi-agent Dynamic Algorithm Configuration

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Abstract

Automated algorithm configuration relieves users from tedious, trial-and-error tuning tasks. A popular algorithm configuration tuning paradigm is dynamic algorithm configuration (DAC), in which an agent learns dynamic configuration policies across instances by reinforcement learning (RL). However, in many complex algorithms, there may exist different types of configuration hyperparameters, and such heterogeneity may bring difficulties for classic DAC which uses a single-agent RL policy. In this paper, we aim to address this issue and propose multi-agent DAC (MA-DAC), with one agent working for one type of configuration hyperparameter. MA-DAC formulates the dynamic configuration of a complex algorithm with multiple types of hyperparameters as a contextual multi-agent Markov decision process and solves it by a cooperative multi-agent RL (MARL) algorithm. To instantiate, we apply MA-DAC to a well-known optimization algorithm for multi-objective optimization problems. Experimental results show the effectiveness of MA-DAC in not only achieving superior performance compared with other configuration tuning approaches based on heuristic rules, multi-armed bandits, and single-agent RL, but also being capable of generalizing to different problem classes. Furthermore, we release the environments in this paper as a benchmark for testing MARL algorithms, with the hope of facilitating the application of MARL.

1 Introduction

Finding right configurations of hyperparameters is critical for many learning and optimization algorithms [21]. Automated methods, such as algorithm configuration (AC) [19, 32], emerge to search for right configurations, with the aim of relieving users from tedious, trial-and-error tuning tasks. However, static configuration policies obtained by AC may not necessarily yield optimal performance (compared with dynamic policies) since algorithms may require different configurations at different stages of their execution [44].

Dynamic algorithm configuration (DAC) [4, 1] is a well-known paradigm for obtaining dynamic configuration policies. Unlike AC, DAC can dynamically adjust the algorithm's configuration during the optimization process, through formulating it as a contextual Markov decision process (MDP) and then solving it by reinforcement learning (RL) [39]. DAC has been found to outperform static methods on many tasks, including the learning rate tuning of deep neural networks [9], step-size adaptation of evolution strategies [41], and heuristic selection of AI planning [44].

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The task of DAC typically focuses on a single type of configuration hyperparameter, such as tuning the step-size in CMA-ES [41]. However, due to the increasing complexity of real-world problem modeling, there are many algorithms whose performance rests on multiple types of hyperparameters. Tuning one type while fixing the rest may not produce promising results. Take a popular evolutionary algorithm for multi-objective optimization problems, MOEA/D [59], as an example. It has four types of configuration hyperparameters: weights, neighborhood size, reproduction operator type, and parameters associated with the reproduction operator used. All of them are critical and significantly affect the performance of the algorithm [51]. Finding a near-optimal configuration combination for each part of these hyperparameters requires massive manual effort [14]. However, how to jointly adjust multiple types of configuration hyperparameters is still an open problem [1].

In this paper, we attempt to extend DAC to deal with tasks with multiple types of configuration hyperparameters. We model this as a cooperative multi-agent problem [34], with each agent handling one type of hyperparameter, for a shared goal (i.e., maximizing the team reward). Specifically, the proposed multi-agent DAC (MA-DAC) method formulates the task as a contextual multi-agent MDP (MMDP) [7], and solves it by a common pay-off cooperative multi-agent RL (MARL) algorithm. As an instantiation, we apply MA-DAC to the multi-objective evolutionary algorithm MOEA/D [59] to learn the right configurations of its four types of hyperparameters by the classic MARL algorithm called value-decomposition networks (VDN) [46].

Experiments on well-established multi-objective optimization problems show that MA-DAC outperforms other configuration tuning methods based on heuristic rules [37], multi-armed bandits [26, 17] and single-agent RL [33]. Furthermore, we demonstrate the generalization ability of the learned MA-DAC policy to both inner classes (different instances with the same number of objectives) and outer classes (different instances with different numbers of objectives). Ablation studies also demonstrate the importance of tuning every type of hyperparameter.

Our contributions are three-fold:

1. To the best of our knowledge, the MA-DAC method is the first one to address the dynamic configuration of algorithms with multiple types of hyperparameters.
2. The contextual MMDP formulation of MA-DAC is analyzed, and experimental results show that the presented formulation works well and has good generalization ability.
3. The instantiation of configuring MOEA/D in this work can be used as a benchmark problem for MARL. The heterogeneity of MOEA/D's hyperparameters and the stochasticity of its search can promote the research of MARL algorithms. Besides, the learned policies are useful for a specific type of optimization task - multi-objective optimization, which will facilitate the application of MARL.

2 Background

2.1 Dynamic algorithm configuration

Different from the static configuration of AC, DAC aims at dynamically adjusting the configuration hyperparameters of an algorithm during its optimization process. Biedenkapp et al. [4] formulated DAC as a contextual MDP $\mathcal{M}_{\mathcal{I}} := \mathcal{M}_{i\sim\mathcal{I}}$ and applied RL to solve it. $\mathcal{I}$ represents the space of problem instances, and each $\mathcal{M}_i := \langle \mathcal{S}, \mathcal{A}, \mathcal{T}_i, r_i \rangle$ [4, 12] corresponds to one target problem instance $i \in \mathcal{I}$. The notion of context $\mathcal{I}$ allows to study generalization of policies in a principled manner [23]. Given a target algorithm A with its configuration hyperparameters space Θ, a DAC policy $\pi \in \Pi$ maps the state $s \in \mathcal{S}$ (e.g., history of changes in the objective value achieved by the target algorithm A) to the action $a \in \mathcal{A}$ (i.e., a hyperparameter $\theta \in \Theta$ of the target algorithm A). DAC aims at improving the performance of A on a set of instances (e.g., optimization functions). Given a probability distribution p over the space $\mathcal{I}$ of problem instances, the objective of DAC is to find an optimal policy π^*. That is,

$$\pi^* \in \arg\min_{\pi\in\Pi} \int_{i\in\mathcal{I}} p(i)c(\pi, i)\mathrm{d}i, \tag{1}$$

where $i \in \mathcal{I}$ is an instance to be optimized, and $c(\pi, i) \in \mathbb{R}$ is the cost function of the target algorithm with policy π on the instance i. It has been shown that DAC outperforms static policies in learning rate adaptation in SGD [9], step-size adaptation in CMA-ES [41], and heuristic selection in planning [44]. These applications all only involve a single type of hyperparameter. Dynamic configurations of complex algorithms with multiple types of hyperparameters have been found to be difficult for current DAC methods [12, 1].

2.2 Multi-agent reinforcement learning

A multi-agent system [56] under fully observable cooperative situation can be modeled as an MMDP [7], which can be formalized as $\mathcal{M} := \langle \mathcal{N}, \mathcal{S}, \{\mathcal{A}_j\}_{j=1}^{n}, \mathcal{T}, r\rangle$, where $\mathcal{N}$ is a set of n agents, $\mathcal{S}$ is the state space, and $\mathcal{A}_j$ is agent j's action space. At each time-step, agent $j \in \mathcal{N}$ acquires $s \in \mathcal{S}$ and then chooses the action $a^{(j)} \in \mathcal{A}_j$. The joint action $\boldsymbol{a} = \langle a^{(1)}, \ldots, a^{(n)}\rangle$ leads to next state $s' \sim \mathcal{T}(\cdot \mid s, \boldsymbol{a})$ and all agents get a shared global reward $r(s, \boldsymbol{a})$.

The goal of an MMDP is to find a joint policy that maps the states to probability distributions over joint actions, $\boldsymbol{\pi} : S \to \Delta(\mathcal{A}_1 \times \mathcal{A}_2 \times \cdots \times \mathcal{A}_n)$, where $\Delta(\mathcal{A}_1 \times \mathcal{A}_2 \times \cdots \times \mathcal{A}_n)$ stands for the distribution over joint actions, with the goal of maximizing the global value function:

$$Q^{\boldsymbol{\pi}}(s, \boldsymbol{a}) = \mathbb{E}_{\boldsymbol{\pi}}\left[\sum_{t=0}^{\infty} \gamma^t r(s_t, \boldsymbol{a}_t) \mid s_0 = s, \boldsymbol{a_0} = \boldsymbol{a}\right]. \tag{2}$$

3 Multi-agent DAC

This section is devoted to the MA-DAC method, where Section 3.1 is concerned with formulating MA-DAC as a contextual MMDP and Section 3.2 explains components of MA-DAC.

3.1 Problem formulation

We propose MA-DAC as a new paradigm for solving the dynamic configuration of algorithms with multiple types of hyperparameters. We formulate MA-DAC as a contextual MMDP $\mathcal{M}_{\mathcal{I}} := \{\mathcal{M}_i\}_{i \sim \mathcal{I}}$, where $\mathcal{M}_i := \langle \mathcal{N}, \mathcal{S}, \{\mathcal{A}_j\}_{j=1}^{n}, \mathcal{T}_i, r_i\rangle$ is a single MMDP as defined in Section 2.2. The notion of context $\mathcal{I}$ induces multiple MMDPs [4, 12]. Each $\mathcal{M}_i$ stands for a specific instance i sampled from a given distribution over $\mathcal{I}$, where an instance $i \in \mathcal{I}$ corresponds to a function f to be optimized. Different $\mathcal{M}_i$s have shared state and action spaces, but with different transitions and reward functions. Algorithms are often tasked with solving different problem instances from the same or similar domains. Searching for well-performing parameter settings on a specific instance might achieve strong performance on that individual instance but might perform poorly in new instances. Therefore, we explicitly take the instance distribution $\mathcal{I}$ as context into account to facilitate generalization [4].

Given a parameterized algorithm A with a configuration space $\Theta = \{\theta_j\}_{j \in \mathcal{N}}$, one agent in MA-DAC is to handle one type of configuration hyperparameter $\theta_j \in \Theta$ and all the agents work with the same goal, i.e., maximizing the team reward. The action space of each agent $j \in \mathcal{N}$ is the hyperparameter space of the corresponding θ_j. Note that MA-DAC can be seen as a common-payoff cooperative MARL problem and can be solved by any cooperative MARL algorithm.

3.2 Components of MA-DAC

Next, we introduce several important components of MA-DAC, including the state, action, transition, reward, and instance set.

State. The state is used to describe the situation of the target algorithm, which is a key component in MA-DAC. We suggest that the state should have the following properties.

1. Accessibility. The state should be accessible in each step during the optimization process.
2. Representation. The state should reflect the information in the optimization process.
3. Generalization. The learned policy is expected to generalize to inner and even outer classes of instances. Thus, the state should consist of the common features across different instances.

Besides, it is better if the state can be easily obtained, reducing the computational cost. Note that some of the above properties of state formulation have also been suggested for DAC [29, 12].

Action. Each agent in MA-DAC focuses on one type of configuration hyperparameter. Its action is the value of the hyperparameter that should be adjusted, which can be discrete or continuous. MA-DAC agents are heterogeneous because they have completely different action spaces and affect different types of hyperparameters of the target algorithm.

Transition. The transition function describes the dynamics of the problem. For an iterative algorithm, each iteration can be defined as a step. Given state s_t, each agent j acts $a_t^{(j)}$, and the probability of reaching state s_{t+1} can be expressed as $\mathcal{T}(s_{t+1} \mid s_t, \boldsymbol{a}_t)$. Different from the state and action spaces, the transition function depends on the given instance $f \in \mathcal{F}$. Thus, the policy should identify the characteristics of the current instance and take the optimal action under it.

Reward. The reward is used to guide the policy's learning process, whose quality has a significant impact on the policy's final performance. Many RL benchmark environments include a well-defined reward function. However, in many application scenarios, we must define the reward function manually based on a specific metric that can indicate the final performance.

Since the goal of an iterative optimization algorithm at iteration t is to find a solution with the best objective function value so far rather than to just find a better solution than the solution at the $t-1$ step (since the quality of solutions in the last step may be poor), it would make sense to give the policy a reward when finding a better solution than the best solution so far (rather than finding a better solution than the solution at the last step). Another factor one may need to consider when designing a reward function is that with time, it is getting harder to find better-quality solutions. In the beginning, it may be easy to achieve rapid improvement of solution quality, but in later stages, improvement could be harder. As such, a reward function that rewards more an agent who can find a better solution in later stages can encourage the agent to find a very good solution in the end. Considering these two factors, we propose the following reward function at step t:

$$r_t = \begin{cases} (1/2) \cdot (p_{t+1}^2 - p_t^2) & \text{if } f(s_{t+1}) < f_t^* \\ 0 & \text{otherwise} \end{cases}, \tag{3}$$

where

$$p_{t+1} = \begin{cases} \frac{f(s_0) - f(s_{t+1})}{f(s_0)} & \text{if } f(s_{t+1}) < f_t^* \\ p_t & \text{otherwise} \end{cases}, \tag{4}$$

and f_t^* is the minimum metric value found until step t.

As shown in Figure 1, the isosceles right-angled triangle indicates the maximum return we can get, where p^* is the largest value of p_t. At step t, the current reward we obtain is the area of the triangle with side length p_{t+1} minus the area of the triangle with side length p_t. The proposed triangle-based reward function has two properties: 1) it only rewards the agent when a new solution is better than the best solution found so far and 2) the reward increases in later stages. The comparative experiment is provided in Appendix B.2. This design may be applicable to a wide range of similar tasks.

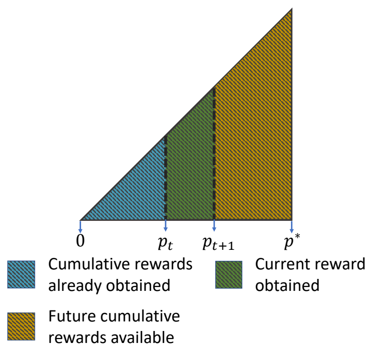
0
p_t
p_{t+1}
p^*
Cumulative rewards already obtained
Current reward obtained
Future cumulative rewards available

Figure 1: Illustration of the reward function.

Instance set. Instance set defines the optimization problem instances that have to be solved by the target algorithm. Note that it is possible to learn policies even across very heterogeneous problem instances by using the context information [4, 41]. Admittedly, if the instances have some similar properties, the learned policy can generalize better [12].

4 Applying MA-DAC to dynamic configuration tuning of MOEA/D

As an instantiation, we apply MA-DAC to a well-established evolutionary algorithm for multi-objective optimization problems, multi-objective evolutionary algorithm based on decomposition (MOEA/D) [59]. As one of the most widely used multi-objective evolutionary algorithms, MOEA/D has several heterogeneous types of configuration hyperparameters (e.g., weights, neighborhood size, and reproduction operator type), which is a good fit for the proposed MA-DAC. We first briefly introduce multi-objective optimization and MOEA/D in Section 4.1, followed by detailed explanations of applying MARL to MOEA/D in Section 4.2, which results in an MARL benchmark, denoted by MaMo. Finally, we compare MaMo with other MARL benchmarks in Section 4.3.

4.1 Multi-objective optimization and MOEA/D

Multi-objective optimization refers to an optimization problem with more than one objective to be considered simultaneously. It is very common in the real world. For example, in deep neural networks, apart from the accuracy, one may also care about the model size, latency, and/or energy consumption [31, 16].

A prominent feature of multi-objective optimization problems (MOPs) is that unlike single-objective optimization problems, in MOPs there is no single optimal solution, but a set of Pareto optimal solutions. A solution is called Pareto optimal if there is no other solution in the search space that dominates it[1]. Unfortunately, the number of Pareto optimal solutions for a given MOP is typically prohibitively large or even infinite. Therefore, the goal of a multi-objective optimization algorithm is to find a good approximation that well represents all the Pareto optimal solutions.

Evolutionary algorithms have demonstrated their effectiveness to solve MOPs. Their population-based nature can approximate the problem's optimal solutions within one execution, with each solution in the population representing a unique trade-off among the objectives. MOEA/D [59] is a representative multi-objective evolutionary algorithm. Unlike other mainstream multi-objective evolutionary algorithms like NSGA-II [10], which compare solutions based on their Pareto dominance relation and density in the population, MOEA/D converts an MOP into a number of single-objective sub-problems through a number of weights, where neighboring solutions work cooperatively for the optimal solutions for the single-objective sub-problems. As such, MOEA/D entails different heterogeneous types of hyperparameters, e.g., weights and neighborhood size. Such hyperparameters significantly affect the performance of the algorithm. For example, different weight distributions are suitable for MOPs with different Pareto front shapes as the weights are used to control the distribution of the final population [28]. A large neighborhood has high search ability in the objective space while a small neighborhood is beneficial for diversity maintenance in the decision space [22]. In short, finding right configurations for these hyperparameters requires massive manual effort and different configurations work well on different MOPs.

Note that some recent efforts have been made to adjust the hyperparameters of MOEA/D by heuristic rules [37], multi-armed bandit [26], and RL [50]. However, they all focus on a single type of hyperparameter, and also very few of them work on the dynamic algorithm configuration well.

4.2 MA-DAC for MOEA/D

In this section, we show how to apply MA-DAC to learn the configuration policy of MOEA/D and also introduce the resulting environment MaMo. Each generation in the evolutionary process of MOEA/D is one step in the MaMo.

The state of MaMo can be divided into three parts.

1. To describe the general properties of the optimization problems, the first part is the features of the problem instance, including the number of variables and objectives.
2. To emphasize the general information of the algorithm, the second part includes the features of the optimization process, i.e., how much computational budget has been used and how many steps of the algorithm have not made any progress.
3. To show the properties of the population and that how the population is evolved, we use several indicators, i.e., hypervolume[2] [61], ratio of non-dominated solutions in the population and average distance of the solutions, in the third part. For each indicator, we also use the gap between the current value and the value corresponding to the last population to

[1]For two solutions x and y, x is called to dominate y, if x is not worse than y on all objectives and better than y on at least one objective.

[2]Hypervolume is a quality indicator that can reflect both convergence and diversity of a solution set [27].

reflect the immediate evolutionary progress. Besides, we use statistic metrics (the mean and standard deviation) of the indicators in several recent steps and all steps from the beginning to measure the short and long histories of the optimization, respectively.

To facilitate the generalization of the learned MA-DAC policy, we have pre-processed some state features. More details about state are provided in Appendix A.2 due to space limitation.

We consider four heterogeneous types of configuration hyperparameters in MOEA/D as the actions of different agents of MA-DAC.

1. Weights. In MOEA/D, weights are used to maintain the diversity of the converted single-objective sub-problems [37]. The action space is discrete with two dimensions, i.e., adjusting (T) and not adjusting (N) the weights. Furthermore, we limit the frequency of adjustment, because too frequent adjustment will lead to drastic changes in the sub-problems and is detrimental to the optimization process.
2. Neighborhood size. The neighborhood size is to control the distance between solutions in mating selection; a small size helps the search exploit the local area while a large size helps the search explore a wide objective space [54]. We discretize the action space into four dimensions. That is, the neighborhood size can be 15, 20, 25 or 30.
3. Types of the reproduction operators. We consider four types of differential evolution (DE) operators. Each type has different search ability [26, 42].
4. Parameters of reproduction operators. The parameters (e.g., scaling factor) of the reproduction operators in MOEA/D significantly affect the algorithm's performance [45], and the action space has four discrete dimensions.

The detailed definitions of the actions are given in Appendix A.3 due to space limitation.

We use the MOPs with similar properties from the well-known MOP benchmarks DTLZ [11] and WFG [18] as the instance set of MaMo. These MOPs can have different number of objectives, and those with the same number of objectives can be seen as inner classes because the number of objectives considerably affects the properties and difficulty level of MOPs. We use the inverted generational distance (IGD) [6] as the metric in Eq. (3), resulting in the reward function.

To learn the policy, we use a classical MARL algorithm named VDN [46], which is widely used in cooperative multi-agent systems. VDN learns to decompose the team value function into agent-wise value functions, alleviating the exponential growth of the action space. It follows the Individual-Global-Max (IGM) principle [43], i.e., the consistency between joint and local greedy action selections by the joint value function $Q_{\mathrm{tot}}(s, \boldsymbol{a})$ and individual value functions $\left[Q_j(s, a^{(j)})\right]_{j=1}^{n}$. All parameters in MA-DAC are updated using the standard TD loss from the global Q-value Q_{tot}, which follows additivity to factorize the global value function, i.e., $Q_{\text{tot}}(s, \boldsymbol{a}) = \sum_{j=1}^{n} Q_j\left(s, a^{(j)}\right)$. In the testing phase, each agent acts greedily with respect to its Q_j.

4.3 Comparison among MARL benchmarks

Table 1: Overview of MARL benchmarks and their properties.

Benchmark	Heterogeneous	#agents	Stochastic	Application scenarios
Matrix Games [8]	×	2	Low	Game
MPE [30]	×	2-3	Low	Game
MAgent [60]	×	2-1000	Low	Game
SMAC [40]	✓	2-30	Low	Game
Active Voltage Control [53]	×	3-38	Low	Control
MaMo (Ours)	✓	2-4	High	Optimization

There are many benchmarks [36, 48] emerged in recent years. In order to clearly show the characteristics of MaMo, we compare it with some MARL benchmarks, as shown in Table 1. Heterogeneity refers to agents having different action spaces or skills [52]. For example, in MaMo, there are four entirely different action spaces, i.e., weights, neighborhood size, types of the reproduction operators and their parameters. Stochasticity means that performing the same action in the same state may lead to a different next state. The high stochasticity of MaMo comes from the randomness of MOEA/D.

The primary benchmarks are designed to investigate different aspects of multi-agent systems. For example, Matrix Games [8] and Multi-Agent Particle Environments (MPE) [30] are popular and classical testbeds, to investigate cooperative or competitive behaviors in small scale settings (with 2–3 agents). MAgent [60] is used to test the scalability of MARL methods, where the number of agents is up to 1000. SMAC [40] has attracted wide attention in recent years to test the coordination ability in cooperative MARL [13, 57, 36]. For the first time, Active Voltage Control [53] creates an exciting yet challenging real-world scenario for the application of MARL. To the best of our knowledge, none of the known benchmarks has focused on highly heterogeneous and stochastic scenarios in MARL. We hope our new MaMo benchmark can offer a good supplement that could benefit the MARL community.

5 Experiments

To examine the effectiveness of MA-DAC, we conduct experiments using MaMo. We investigate the following research questions (RQs). RQ1: How does MA-DAC perform compared with the baseline and other tuning algorithms? RQ2: How is the generalization ability of MA-DAC? RQ3: How do the different parts of MA-DAC affect the performance? We introduce the experimental settings in Section 5.1, and investigate the above RQs in Section 5.2.

5.1 Experimental settings

We consider several well-established multi-objective test functions (DTLZ2, DTLZ4 and WFG4-WFG9) with 3, 5 and 7 objectives following the practice in Bezerra et al. [3] to examine our method. In all of the following experiments, several arbitrary functions (here DTLZ2, WFG4 and WFG6) from the function set are used as the training set, and all the other functions are considered as the testing set. Note that "train" and "test" in the tables mean that the comparison is based on the training (i.e., DTLZ2, WFG4 and WFG6) and testing (i.e., DTLZ4, WFG5, WFG7, WFG8 and WFG9) problems, respectively. IGD [6] is considered as the metric to measure the performance of the algorithms. The mean and standard deviation of the IGD values obtained by each algorithm on each MOP for 30 independent runs are reported. We apply the Wilcoxon rank-sum test with significance level 0.05. For a fair comparison, other parameters (such as population size and computational budget) are set to be the same across all the compared algorithms. More details about the settings can be found in Appendix B.1 due to space limitation. Our code is available at `https://github.com/lamda-bbo/madac`.

5.2 Experimental results

RQ1: How does MA-DAC perform compared with the baseline and other tuning algorithms? We compare the MA-DAC policy with the original MOEA/D [59], DQN [33] and MA-UCB [17]. DQN is a single-agent RL algorithm that shares the same state, reward, and transition as our MA-DAC but has a different action space that is the concatenation of the four types of hyperparameters. DQN can be seen as an instantiation of DAC in MaMo. MA-UCB is a simplified algorithm that uses four UCB agents to adjust the four types of hyperparameters. For MA-DAC and DQN, we perform the training and testing on the problems with the number of objectives.

The results are shown in Table 2. As can be seen in the table, MA-DAC is significantly superior to the other algorithms on almost all the 24 problems. Furthermore, MA-DAC (which is trained only on DTLZ2, WFG4 and WFG6) shows excellent performance on previously unseen problems during the training process, demonstrating its good generalization ability. DQN policy is significantly worse than MA-DAC on all the problems, which is consistent with the previous observation that DQN performs poorly in MARL tasks [15]. DQN suffers from the exponentially increasing action space with the number of agents [34, 58], while MA-DAC effectively decomposes the action space, making each agent much easier to find their own near-optimal policy and then leading to a good joint policy. The superiority of MA-DAC over MA-UCB also demonstrates the necessity of learning configuration policy by an MARL algorithm.

Table 2: IGD values obtained by MOEA/D, DQN, MA-UCB and MA-DAC on different problems. Each result consists of the mean and standard deviation of 30 runs. The best mean value on each problem is highlighted in **bold**. The symbols '$+$', '$-$' and '$\approx$' indicate that the result is significantly superior to, inferior to, and almost equivalent to MA-DAC, respectively, according to the Wilcoxon rank-sum test with significance level 0.05.

Problem	M	MOEA/D	DQN	MA-UCB	MA-DAC
DTLZ2	3	4.605E-02 (3.54E-04) $-$	4.628E-02 (2.96E-04) $-$	4.671E-02 (3.70E-04) $-$	**3.807E-02** (5.05E-04)
	5	3.006E-01 (1.55E-03) $-$	3.016E-01 (1.34E-03) $-$	3.041E-01 (1.69E-03) $-$	**2.442E-01** (1.26E-02)
	7	4.455E-01 (1.41E-02) $-$	4.671E-01 (1.15E-02) $-$	4.826E-01 (9.59E-03) $-$	**3.944E-01** (1.17E-02)
WFG4	3	5.761E-02 (5.41E-04) $-$	6.920E-02 (1.20E-03) $-$	7.165E-02 (1.83E-03) $-$	**5.200E-02** (1.19E-03)
	5	3.442E-01 (1.21E-02) $-$	2.810E-01 (6.86E-03) $-$	2.859E-01 (6.77E-03) $-$	**1.868E-01** (2.81E-03)
	7	4.529E-01 (1.79E-02) $-$	3.725E-01 (1.14E-02) $-$	3.868E-01 (1.54E-02) $-$	**3.033E-01** (3.66E-03)
WFG6	3	6.938E-02 (5.50E-03) $-$	6.834E-02 (1.78E-02) $-$	6.601E-02 (1.00E-02) $-$	**4.831E-02** (8.95E-03)
	5	3.518E-01 (2.82E-03) $-$	3.160E-01 (2.40E-02) $-$	3.359E-01 (1.47E-02) $-$	**1.942E-01** (6.90E-03)
	7	4.869E-01 (3.03E-02) $-$	4.322E-01 (2.95E-02) $-$	4.389E-01 (3.41E-02) $-$	**3.112E-01** (4.93E-03)
Train: $+/-/\approx$		0/9/0	0/9/0	0/9/0	
DTLZ4	3	6.231E-02 (8.85E-02) $\approx$	**5.590E-02** (5.77E-03) $-$	6.011E-02 (5.08E-03) $-$	6.700E-02 (6.14E-02)
	5	3.133E-01 (4.45E-02) $\approx$	3.457E-01 (1.61E-02) $-$	3.492E-01 (1.69E-02) $-$	**2.995E-01** (2.10E-02)
	7	4.374E-01 (2.57E-02) $-$	4.552E-01 (1.47E-02) $-$	4.756E-01 (2.01E-02) $-$	**4.182E-01** (1.21E-02)
WFG5	3	6.327E-02 (1.10E-03) $-$	6.212E-02 (5.54E-04) $-$	6.118E-02 (7.03E-04) $-$	**4.730E-02** (7.89E-04)
	5	3.350E-01 (9.77E-03) $-$	3.077E-01 (6.36E-03) $-$	3.036E-01 (8.83E-03) $-$	**1.811E-01** (3.02E-03)
	7	4.101E-01 (2.08E-02) $-$	4.996E-01 (1.32E-02) $-$	5.024E-01 (1.38E-02) $-$	**3.206E-01** (8.04E-03)
WFG7	3	5.811E-02 (6.31E-04) $-$	5.930E-02 (7.32E-04) $-$	6.014E-02 (7.11E-04) $-$	**4.066E-02** (5.31E-04)
	5	3.572E-01 (5.47E-03) $-$	2.993E-01 (1.43E-02) $-$	3.207E-01 (1.71E-02) $-$	**1.858E-01** (2.12E-03)
	7	5.236E-01 (2.19E-02) $-$	4.576E-01 (2.38E-02) $-$	4.879E-01 (2.75E-02) $-$	**3.258E-01** (1.25E-02)
WFG8	3	8.646E-02 (3.44E-03) $-$	9.280E-02 (1.06E-03) $-$	9.612E-02 (1.48E-03) $-$	**7.901E-02** (1.19E-03)
	5	4.258E-01 (8.42E-03) $-$	3.969E-01 (1.26E-02) $-$	3.956E-01 (1.32E-02) $-$	**2.479E-01** (7.20E-03)
	7	5.816E-01 (1.30E-02) $-$	5.575E-01 (1.39E-02) $-$	5.642E-01 (1.38E-02) $-$	**4.127E-01** (5.93E-03)
WFG9	3	5.817E-02 (1.24E-03) $-$	5.628E-02 (7.29E-04) $-$	7.953E-02 (2.45E-02) $-$	**4.159E-02** (6.10E-04)
	5	3.633E-01 (1.20E-02) $-$	3.258E-01 (1.61E-02) $-$	3.396E-01 (1.55E-02) $-$	**1.832E-01** (7.10E-03)
	7	5.538E-01 (2.63E-02) $-$	5.115E-01 (2.15E-02) $-$	5.227E-01 (1.79E-02) $-$	**3.278E-01** (7.21E-03)
Test: $+/-/\approx$		0/13/2	0/15/0	0/15/0	

We also compare our algorithm with two adaptive MOEA/D algorithms, i.e., MOEA/D-FRRMAB [26] and MOEA/D-AWA [37], which adjust reproduction operator types and weights based on MAB and heuristic rules, respectively. The results clearly show the superior performance of MA-DAC, and are provided in Appendix B.3 and Appendix B.4 due to space limitation.

RQ2: How is the generalization ability of MA-DAC? We compare MA-DAC policies trained from different training sets to test the generalization ability of MA-DAC policies. MA-DAC (M) denotes that the policy is trained on the problems (i.e., DTLZ2, WFG4 and WFG6) with all 3, 5 and 7 objectives. Meanwhile, MA-DAC (3), (5) and (7) denote that the policies are trained on the problems (i.e., DTLZ2, WFG4 and WFG6) with 3, 5 and 7 objectives, respectively.

As shown in Table 3, it is unsurprising that the results of average rank show that the MA-DAC (3), (5) and (7) policies have excellent performance on the problems with 3, 5 and 7 objectives, respectively. For example, MA-DAC (7) has the best average rank (i.e., 1.0) on the test problems with 7 objectives, but has the worst average rank (i.e., 4.0) on the problems with 3 objectives. To obtain a more robust policy, we mix the problems with different number of objectives as the training set, resulting in the MA-DAC (M). As can be seen in Table 3, MA-DAC (M) demonstrates its robustness. Among all the policies, MA-DAC (M) takes the first, third, and second places in terms of its performance in the three types of problems, respectively. Lastly, the last row of the table shows the outperformance of these MA-DAC policies compared with other policies – the IGD values of all the four MA-DAC policies perform significantly better than the best result obtained by the three peer algorithms MOEA/D, DQN and MA-UCB in Table 2.

RQ3: How do the different parts of MA-DAC affect the performance? We conduct ablation studies to show the importance of different types of hyperparameters, and the results are given in Table 4. We use MA-DAC (M) w/o i to denote the MA-DAC policy that does not include the i-th agent, and we use a reasonable setting as the default for each ablated agent; the detailed settings are

Table 3: IGD values obtained by MA-DAC (M), MA-DAC (3), MA-DAC (5) and MA-DAC (7) on different problems. Each result consists of the mean and standard deviation of 30 runs. The best mean value on each problem is highlighted in **bold**. The symbols '$+$', '$-$' and '$\approx$' indicate that the result is significantly superior to, inferior to, and almost equivalent to the best value except for MA-DAC in Table 2, respectively, according to the Wilcoxon rank-sum test with significance level 0.05.

Problem	M	MA-DAC (M)	MA-DAC (3)	MA-DAC (5)	MA-DAC (7)
DTLZ2	3	3.839E-02 (5.35E-04) $+$	**3.807E-02** (5.05E-04) $+$	3.830E-02 (7.24E-04) $+$	3.837E-02 (5.69E-04) $+$
	5	2.468E-01 (7.55E-03) $+$	2.472E-01 (1.56E-02) $+$	**2.442E-01** (1.26E-02) $+$	2.569E-01 (1.39E-02) $+$
	7	3.921E-01 (8.84E-03) $+$	**3.880E-01** (1.02E-02) $+$	4.081E-01 (1.52E-02) $+$	3.944E-01 (1.17E-02) $+$
WFG4	3	5.220E-02 (9.83E-04) $+$	**5.200E-02** (1.19E-03) $+$	5.236E-02 (1.10E-03) $+$	5.302E-02 (9.78E-04) $+$
	5	**1.850E-01** (3.14E-03) $+$	1.867E-01 (3.01E-03) $+$	1.868E-01 (2.81E-03) $+$	1.853E-01 (2.67E-03) $+$
	7	3.091E-01 (5.80E-03) $+$	3.104E-01 (7.14E-03) $+$	3.100E-01 (5.89E-03) $+$	**3.033E-01** (3.66E-03) $+$
WFG6	3	5.078E-02 (1.20E-02) $+$	4.831E-02 (8.95E-03) $+$	**4.599E-02** (9.48E-03) $+$	5.206E-02 (1.64E-02) $+$
	5	1.971E-01 (6.40E-03) $+$	2.003E-01 (6.26E-03) $+$	**1.942E-01** (6.90E-03) $+$	1.957E-01 (6.67E-03) $+$
	7	3.114E-01 (5.08E-03) $+$	3.242E-01 (9.24E-03) $+$	3.129E-01 (5.71E-03) $+$	**3.112E-01** (4.93E-03) $+$
DTLZ4	3	**6.171E-02** (3.67E-02) $+$	6.700E-02 (6.14E-02) $+$	6.618E-02 (4.62E-02) $+$	8.088E-02 (7.12E-02) $+$
	5	3.044E-01 (1.66E-02) $\approx$	**2.974E-01** (1.94E-02) $+$	2.995E-01 (2.10E-02) $\approx$	3.036E-01 (1.69E-02) $\approx$
	7	4.271E-01 (1.45E-02) $+$	4.313E-01 (1.39E-02) $\approx$	4.327E-01 (2.15E-02) $\approx$	**4.182E-01** (1.21E-02) $+$
WFG5	3	**4.721E-02** (7.15E-04) $+$	4.730E-02 (7.89E-04) $+$	4.733E-02 (8.10E-04) $+$	4.746E-02 (5.90E-04) $+$
	5	1.811E-01 (2.59E-03) $+$	1.817E-01 (2.96E-03) $+$	1.811E-01 (3.02E-03) $+$	**1.808E-01** (2.83E-03) $+$
	7	3.256E-01 (5.49E-03) $+$	3.266E-01 (8.98E-03) $+$	3.263E-01 (9.73E-03) $+$	**3.206E-01** (8.04E-03) $+$
WFG7	3	4.076E-02 (5.33E-04) $+$	**4.066E-02** (5.31E-04) $+$	4.077E-02 (5.12E-04) $+$	4.124E-02 (4.98E-04) $+$
	5	1.839E-01 (2.38E-03) $+$	1.881E-01 (3.70E-03) $+$	1.858E-01 (2.12E-03) $+$	**1.836E-01** (2.21E-03) $+$
	7	3.368E-01 (1.54E-02) $+$	3.461E-01 (1.97E-02) $+$	3.390E-01 (1.38E-02) $+$	**3.258E-01** (1.25E-02) $+$
WFG8	3	**7.828E-02** (1.46E-03) $+$	7.901E-02 (1.19E-03) $+$	7.921E-02 (1.36E-03) $+$	7.944E-02 (1.30E-03) $+$
	5	2.506E-01 (1.11E-02) $+$	2.653E-01 (1.51E-02) $+$	**2.479E-01** (7.20E-03) $+$	2.532E-01 (9.28E-03) $+$
	7	4.303E-01 (1.49E-02) $+$	4.364E-01 (1.38E-02) $+$	4.242E-01 (9.08E-03) $+$	**4.127E-01** (5.93E-03) $+$
WFG9	3	4.324E-02 (7.07E-04) $+$	**4.159E-02** (6.10E-04) $+$	4.359E-02 (1.00E-02) $+$	6.415E-02 (2.64E-02) $+$
	5	1.858E-01 (7.63E-03) $+$	**1.814E-01** (4.59E-03) $+$	1.832E-01 (7.10E-03) $+$	1.918E-01 (1.13E-02) $+$
	7	3.328E-01 (1.02E-02) $+$	3.298E-01 (1.03E-02) $+$	3.307E-01 (1.37E-02) $+$	**3.278E-01** (7.21E-03) $+$
Test: average rank	3	1.4	1.8	2.8	4.0
	5	2.6	2.8	2.2	2.4
	7	2.6	3.4	3.0	1.0
Test: $+/-/\approx$	3	5/0/0	5/0/0	5/0/0	5/0/0
	5	4/0/1	5/0/0	4/0/1	4/0/1
	7	5/0/0	4/0/1	4/0/1	5/0/0

provided in Appendix B.1. That is, MA-DAC (M) w/o 1, 2, 3 and 4 represent MA-DAC (M) without tuning weights, neighborhood size, types of reproduction operators, and parameters of reproduction operators, respectively.

As can be seen in Table 4. MA-DAC (M) outperforms all the ablations, demonstrating the importance of tuning every type of hyperparameter. Note that the column of MA-DAC (M) in Table 4 is just as same as that in Table 3. On the other hand, we notice that the importance of hyperparameters varies. For example, adaptive weights are in general more important as the performance of MA-DAC (M) w/o 1 drops significantly.

Further studies Due to the space limitation, more experiments on MaMo and DACBench [12] are provided in Appendix B and Appendix C, respectively.

- To show the effectiveness of the proposed triangle-based reward function, we compare it with different reward functions in Appendix B.2.
- We give a detailed analysis of the reproduction operators and the adaptive weights in Appendix B.3 and Appendix B.4, respectively.
- To show the optimization process of each method, we plot the curves of IGD value of different methods (i.e., MOEA/D, MOEA/D-FRRMAB, MOEA/D-AWA, DQN, MA-UCB and MA-DAC) in Appendix B.5.
- To improve the compared baseline, we use DQN to dynamically adjust each type of hyper-parameter of MOEA/D in Appendix B.6.
- We use two more MARL algorithms as the implementations of policy networks, i.e., Independent Q Learning (IQL) [47] and QMIX [38] in Appendix B.7.

Table 4: IGD values obtained by MA-DAC (M) w/o 1, MA-DAC (M) w/o 2, MA-DAC (M) w/o 3 and MA-DAC (M) w/o 4 on different problems. Each result consists of the mean and standard deviation of 30 runs. The best mean value on each problem is highlighted in **bold**. The symbols '$+$', '$-$' and '$\approx$' indicate that the result is significantly superior to, inferior to, and almost equivalent to MA-DAC (M), respectively, according to the Wilcoxon rank-sum test with significance level 0.05.

Problem	M	MA-DAC (M) w/o 1	MA-DAC (M) w/o 2	MA-DAC (M) w/o 3	MA-DAC (M) w/o 4	MA-DAC (M)
DTLZ2	3	4.656E-02 (3.80E-04) $-$	3.914E-02 (8.43E-04) $-$	3.935E-02 (6.72E-04) $-$	3.919E-02 (5.91E-04) $-$	**3.839E-02** (5.35E-04)
	5	3.086E-01 (7.24E-03) $-$	2.619E-01 (8.99E-03) $-$	2.503E-01 (1.30E-02) $-$	**2.433E-01** (1.59E-02) $\approx$	2.468E-01 (7.55E-03)
	7	4.970E-01 (1.26E-02) $-$	4.067E-01 (1.20E-02) $-$	4.003E-01 (1.19E-02) $-$	4.228E-01 (1.25E-02) $-$	**3.921E-01** (8.84E-03)
WFG4	3	7.222E-02 (1.93E-03) $-$	5.484E-02 (1.01E-03) $-$	5.410E-02 (8.85E-04) $-$	5.410E-02 (8.85E-04) $-$	**5.220E-02** (9.83E-04)
	5	2.868E-01 (1.01E-02) $-$	1.879E-01 (3.76E-03) $\approx$	**1.845E-01** (2.17E-03) $+$	1.846E-01 (2.39E-03) $+$	1.850E-01 (3.14E-03)
	7	3.758E-01 (1.33E-02) $-$	3.102E-01 (6.34E-03) $-$	**3.020E-01** (3.99E-03) $\approx$	3.032E-01 (4.32E-03) $\approx$	3.091E-01 (5.80E-03)
WFG6	3	6.864E-02 (8.14E-03) $-$	5.338E-02 (1.37E-02) $-$	6.543E-02 (1.69E-02) $-$	6.067E-02 (2.11E-02) $\approx$	**5.078E-02** (1.20E-02)
	5	3.480E-01 (1.34E-02) $-$	2.005E-01 (5.21E-03) $-$	1.996E-01 (6.51E-03) $-$	1.979E-01 (6.76E-03) $-$	**1.971E-01** (6.40E-03)
	7	4.784E-01 (3.37E-02) $-$	3.147E-01 (5.85E-03) $-$	3.162E-01 (6.15E-03) $-$	3.147E-01 (5.73E-03) $-$	**3.114E-01** (5.08E-03)
Train: $+/-/\approx$		0/9/0	0/8/1	1/7/1	1/5/3	
DTLZ4	3	6.463E-02 (3.85E-02) $-$	6.242E-02 (4.07E-02) $-$	**4.496E-02** (2.45E-03) $+$	4.496E-02 (2.45E-03) $+$	6.171E-02 (3.67E-02)
	5	3.497E-01 (1.41E-02) $-$	3.061E-01 (2.12E-02) $\approx$	3.054E-01 (1.55E-02) $\approx$	3.130E-01 (1.81E-02) $-$	**3.044E-01** (1.66E-02)
	7	4.853E-01 (1.82E-02) $-$	4.275E-01 (1.90E-02) $-$	**4.208E-01** (1.52E-02) $\approx$	4.289E-01 (2.07E-02) $-$	4.271E-01 (1.45E-02)
WFG5	3	6.189E-02 (7.40E-04) $-$	4.827E-02 (6.31E-04) $-$	4.766E-02 (5.72E-04) $\approx$	4.766E-02 (5.72E-04) $\approx$	**4.721E-02** (7.15E-04)
	5	3.202E-01 (9.77E-03) $-$	1.821E-01 (2.73E-03) $\approx$	1.835E-01 (2.90E-03) $-$	1.822E-01 (2.31E-03) $-$	**1.811E-01** (2.59E-03)
	7	4.948E-01 (1.47E-02) $-$	3.290E-01 (8.87E-03) $-$	3.310E-01 (7.70E-03) $-$	3.261E-01 (9.26E-03) $-$	**3.256E-01** (5.49E-03)
WFG7	3	6.004E-02 (9.45E-04) $-$	4.250E-02 (5.82E-04) $-$	4.150E-02 (6.60E-04) $-$	4.150E-02 (6.60E-04) $-$	**4.076E-02** (5.33E-04)
	5	3.402E-01 (2.49E-02) $-$	1.873E-01 (3.67E-03) $\approx$	**1.826E-01** (2.60E-03) $+$	1.847E-01 (2.80E-03) $\approx$	1.839E-01 (2.38E-03)
	7	4.877E-01 (5.70E-02) $-$	3.393E-01 (1.23E-02) $-$	3.373E-01 (1.16E-02) $-$	3.377E-01 (1.59E-02) $-$	**3.368E-01** (1.54E-02)
WFG8	3	9.661E-02 (1.87E-03) $-$	8.374E-02 (1.70E-03) $-$	8.029E-02 (1.29E-03) $-$	8.029E-02 (1.29E-03) $-$	**7.828E-02** (1.46E-03)
	5	4.119E-01 (1.30E-02) $-$	2.695E-01 (1.49E-02) $-$	2.571E-01 (1.09E-02) $-$	2.632E-01 (9.96E-03) $-$	**2.506E-01** (1.11E-02)
	7	5.830E-01 (1.59E-02) $-$	4.345E-01 (9.27E-03) $-$	**4.260E-01** (8.71E-03) $-$	4.322E-01 (1.12E-02) $-$	4.303E-01 (1.49E-02)
WFG9	3	5.894E-02 (9.24E-04) $-$	**4.321E-02** (7.50E-04) $-$	4.650E-02 (1.40E-02) $-$	4.650E-02 (1.40E-02) $-$	4.324E-02 (7.07E-04)
	5	3.148E-01 (2.06E-02) $-$	1.875E-01 (5.14E-03) $-$	1.941E-01 (6.45E-03) $-$	1.865E-01 (9.02E-03) $-$	**1.858E-01** (7.63E-03)
	7	5.069E-01 (2.53E-02) $-$	3.433E-01 (1.35E-02) $-$	3.402E-01 (1.00E-02) $-$	3.368E-01 (1.05E-02) $-$	**3.328E-01** (1.02E-02)
Test: $+/-/\approx$		0/15/0	0/12/3	2/10/3	1/12/2	

- We also conduct experiments on Sigmoid from DACBench [12] in Appendix C, which can generate instance sets with a wide range of difficulties. We conduct experiments on the $5D$-Sigmoid and $10D$-Sigmoid (i.e., there are 5 and 10 agents in MA-DAC, respectively) with action space size 3 (i.e., each agent has a 3-dimensional discrete action space). The experimental results show the versatility and scalability of MA-DAC.

6 Conclusion

This paper considers the dynamic configuration of algorithms with multiple types of hyperparameters. We propose MA-DAC to solve it, where one agent works to handle one type of configuration hyperparameter. Experimental results show that MA-DAC works well and has good generalization ability. The instantiation of configuring MOEA/D forms the benchmark MaMo for MARL, with the hope of facilitating the application of MARL.

Considering the superior performance of MA-DAC in many empirical studies, a very interesting future work is to perform theoretical analysis, to better understand why MA-DAC can work. Particularly, many MARL algorithms follow the IGM principle that assumes the global Q is factorizable, while it is not yet clear whether DAC problems are (approximately) factorizable and if using MARL rather than single-agent RL has more advantages. In addition, we will try to propose better contextual MMDP formulation and better cooperative MARL algorithms based on the heterogeneity and stochasticity of MA-DAC. It is also interesting to include more real-world optimization problems into MaMo.

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References

[1] Steven Adriaensen, André Biedenkapp, Gresa Shala, Noor Awad, Theresa Eimer, Marius Lindauer, and Frank Hutter. Automated dynamic algorithm configuration. *arXiv preprint arXiv:2205.13881*, 2022.

[2] Peter Auer. Using confidence bounds for exploitation-exploration trade-offs. *Journal of Machine Learning Research*, 3:397–422, 2002.

[3] Leonardo C. T. Bezerra, Manuel López-Ibáñez, and Thomas Stützle. A large-scale experimental evaluation of high-performing multi- and many-objective evolutionary algorithms. *Evolutionary Computation*, 26(4):621–656, 2018.

[4] André Biedenkapp, H. Furkan Bozkurt, Theresa Eimer, Frank Hutter, and Marius Lindauer. Dynamic algorithm configuration: Foundation of a new meta-algorithmic framework. In *Proceedings of the 24th European Conference on Artificial Intelligence*, pages 427–434, Santiago de Compostela, Spain, 2020.

[5] André Biedenkapp, Nguyen Dang, Martin S Krejca, Frank Hutter, and Carola Doerr. Theory-inspired parameter control benchmarks for dynamic algorithm configuration. In *Proceedings of the 24th Genetic and Evolutionary Computation Conference*, page 766–775, Boston, MA, 2022.

[6] Peter A. N. Bosman and Dirk Thierens. The balance between proximity and diversity in multiobjective evolutionary algorithms. *IEEE Transactions on Evolutionary Computation*, 7(2): 174–188, 2003.

[7] Craig Boutilier. Planning, learning and coordination in multiagent decision processes. In *Proceedings of the 6th Conference on Theoretical Aspects of Rationality and Knowledge*, pages 195–210, De Zeeuwse Stromen, The Netherlands, 1996.

[8] Caroline Claus and Craig Boutilier. The dynamics of reinforcement learning in cooperative multiagent systems. In *Proceedings of the 15th National Conference on Artificial Intelligence and 10th Innovative Applications of Artificial Intelligence Conference*, pages 746–752, Madison, WI, 1998.

[9] Christian Daniel, Jonathan Taylor, and Sebastian Nowozin. Learning step size controllers for robust neural network training. In *Proceedings of the 30th AAAI Conference on Artificial Intelligence*, pages 1519–1525, Phoenix, Arizona, 2016.

[10] Kalyanmoy Deb, Samir Agrawal, Amrit Pratap, and T. Meyarivan. A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, 6(2): 182–197, 2002.

[11] Kalyanmoy Deb, Lothar Thiele, Marco Laumanns, and Eckart Zitzler. Scalable multi-objective optimization test problems. In *Proceedings of the 2002 Congress on Evolutionary Computation*, pages 825–830, Honolulu, HI, 2002.

[12] Theresa Eimer, André Biedenkapp, Maximilian Reimer, Steven Adriaensen, Frank Hutter, and Marius Lindauer. DACBench: A benchmark library for dynamic algorithm configuration. In *Proceedings of the 30th International Joint Conference on Artificial Intelligence*, pages 1668–1674, Montreal, Canada, 2021.

[13] Rihab Gorsane, Omayma Mahjoub, Ruan de Kock, Roland Dubb, Siddarth Singh, and Arnu Pretorius. Towards a standardised performance evaluation protocol for cooperative marl. *arXiv preprint arXiv:2209.10485*, 2022.

[14] Alessio Greco, Salvatore Danilo Riccio, Jon Timmis, and Giuseppe Nicosia. Assessing algorithm parameter importance using global sensitivity analysis. In *Proceedings of International Symposium on Experimental Algorithms - Special Event*, pages 392–407, Kalamata, Greece, 2019.

[15] Pablo Hernandez-Leal, Bilal Kartal, and Matthew E Taylor. A survey and critique of multiagent deep reinforcement learning. *Autonomous Agents and Multi-Agent Systems*, 33(6):750–797, 2019.

[16] Wenjing Hong, Peng Yang, Yiwen Wang, and Ke Tang. Multi-objective magnitude-based pruning for latency-aware deep neural network compression. In *Proceedings of the 16th International Conference on Parallel Problem Solving from Nature*, pages 470–483, Leiden, The Netherlands, 2020.

[17] Safwan Hossain, Evi Micha, and Nisarg Shah. Fair algorithms for multi-agent multi-armed bandits. In *Advances in Neural Information Processing Systems 34*, pages 24005–24017, Virtual, 2021.

[18] Simon Huband, Philip Hingston, Luigi Barone, and Lyndon While. A review of multiobjective test problems and a scalable test problem toolkit. *IEEE Transactions on Evolutionary Computation*, 10(5):477–506, 2006.

[19] Frank Hutter, Holger H. Hoos, Kevin Leyton-Brown, and Thomas Stützle. Paramils: An automatic algorithm configuration framework. *Journal of Artificial Intelligence Research*, 36: 267–306, 2009.

[20] Frank Hutter, Holger H. Hoos, and Kevin Leyton-Brown. Sequential model-based optimization for general algorithm configuration. In *Proceedings of the 5th International conference on learning and intelligent optimization*, pages 507–523, Rome, Italy, 2011.

[21] Frank Hutter, Lars Kotthoff, and Joaquin Vanschoren. *Automated Machine Learning: Methods, Systems, Challenges*. Springer, 2019.

[22] Hisao Ishibuchi, Naoya Akedo, and Yusuke Nojima. Relation between neighborhood size and MOEA/D performance on many-objective problems. In *Proceedings of the 7th International Conference on Evolutionary Multi-Criterion Optimization*, pages 459–474, Sheffield, UK, 2013.

[23] Robert Kirk, Amy Zhang, Edward Grefenstette, and Tim Rocktäschel. A survey of generalisation in deep reinforcement learning. *arXiv preprint arXiv:2111.09794*, 2021.

[24] Saku Kukkonen and Kalyanmoy Deb. A fast and effective method for pruning of non-dominated solutions in many-objective problems. In *Proceedings of the 9th International Conference on Parallel Problem Solving from Nature*, pages 553–562, Reykjavik, Iceland, 2006.

[25] Ke Li. Decomposition multi-objective evolutionary optimization: From state-of-the-art to future opportunities. *arXiv preprint arXiv:2108.09588*, 2021.

[26] Ke Li, Alvaro Fialho, Sam Kwong, and Qingfu Zhang. Adaptive operator selection with bandits for a multiobjective evolutionary algorithm based on decomposition. *IEEE Transactions on Evolutionary Computation*, 18(1):114–130, 2013.

[27] Miqing Li and Xin Yao. Quality evaluation of solution sets in multiobjective optimisation: A survey. *ACM Computing Surveys*, 52(2):1–38, 2019.

[28] Miqing Li and Xin Yao. What weights work for you? Adapting weights for any Pareto front shape in decomposition-based evolutionary multiobjective optimisation. *Evolutionary Computation*, 28(2):227–253, 2020.

[29] Marius Lindauer and André Biedenkapp. Algorithm configuration: Challenges, methods and perspectives. Tutorial on PPSN 2020 and IJCAI 2020.

[30] Ryan Lowe, Yi Wu, Aviv Tamar, Jean Harb, Pieter Abbeel, and Igor Mordatch. Multi-agent actor-critic for mixed cooperative-competitive environments. In *Advances in Neural Information Processing Systems 30*, pages 6379–6390, Long Beach, CA, 2017.

[31] Zhichao Lu, Kalyanmoy Deb, Erik D. Goodman, Wolfgang Banzhaf, and Vishnu Naresh Boddeti. Nsganetv2: Evolutionary multi-objective surrogate-assisted neural architecture search. In *Proceddings of 16th European Conference on Computer Vision*, pages 35–51, Glasgow, UK, 2020.

[32] Manuel López-Ibáñez, Jérémie Dubois-Lacoste, Leslie Pérez Cáceres, Mauro Birattari, and Thomas Stützle. The irace package: Iterated racing for automatic algorithm configuration. *Operations Research Perspectives*, 3:43–58, 2016.

[33] Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Andrei A. Rusu, Joel Veness, Marc G. Bellemare, Alex Graves, Martin A. Riedmiller, Andreas Fidjeland, Georg Ostrovski, Stig Petersen, Charles Beattie, Amir Sadik, Ioannis Antonoglou, Helen King, Dharshan Kumaran, Daan Wierstra, Shane Legg, and Demis Hassabis. Human-level control through deep reinforcement learning. *Nature*, 518(7540):529–533, 2015.

[34] Afshin OroojlooyJadid and Davood Hajinezhad. A review of cooperative multi-agent deep reinforcement learning. *arXiv preprint arXiv:1908.03963*, 2019.

[35] Georgios Papoudakis, Filippos Christianos, Arrasy Rahman, and Stefano V Albrecht. Dealing with non-stationarity in multi-agent deep reinforcement learning. *arXiv preprint arXiv:1906.04737*, 2019.

[36] Georgios Papoudakis, Filippos Christianos, Lukas Schäfer, and Stefano V. Albrecht. Benchmarking multi-agent deep reinforcement learning algorithms in cooperative tasks. In *Proceedings of the Neural Information Processing Systems Track on Datasets and Benchmarks*, pages 1–13, Virtual, 2021.

[37] Yutao Qi, Xiaoliang Ma, Fang Liu, Licheng Jiao, Jianyong Sun, and Jianshe Wu. MOEA/D with adaptive weight adjustment. *Evolutionary Computation*, 22(2):231–264, 2014.

[38] Tabish Rashid, Mikayel Samvelyan, Christian Schroeder, Gregory Farquhar, Jakob Foerster, and Shimon Whiteson. Qmix: Monotonic value function factorisation for deep multi-agent reinforcement learning. In *Proceedings of the 35th International Conference on Machine Learning*, pages 4295–4304, Stockholm, Sweden, 2018.

[39] Sutton Richard S. and Andrew G. Barto. *Reinforcement Learning: An Introduction*. MIT Press, 2018.

[40] Mikayel Samvelyan, Tabish Rashid, Christian Schroeder de Witt, Gregory Farquhar, Nantas Nardelli, Tim GJ Rudner, Chia-Man Hung, Philip HS Torr, Jakob Foerster, and Shimon Whiteson. The starcraft multi-agent challenge. In *Proceedings of the 18th International Conference on Autonomous Agents and MultiAgent Systems*, pages 2186–2188, Montreal, Canada, 2019.

[41] Gresa Shala, André Biedenkapp, Noor H. Awad, Steven Adriaensen, Marius Lindauer, and Frank Hutter. Learning step-size adaptation in CMA-ES. In *Proceedings of the 16th International Conference on Parallel Problem Solving from Nature*, pages 691–706, Leiden, The Netherlands, 2020.

[42] Mudita Sharma, Alexandros Komninos, Manuel López-Ibáñez, and Dimitar Kazakov. Deep reinforcement learning based parameter control in differential evolution. In *Proceedings of the 21st Genetic and Evolutionary Computation Conference*, pages 709–717, Prague, Czech Republic, 2019.

[43] Kyunghwan Son, Daewoo Kim, Wan Ju Kang, David Hostallero, and Yung Yi. QTRAN: Learning to factorize with transformation for cooperative multi-agent reinforcement learning. In *Proceedings of the 36th International Conference on Machine Learning*, pages 5887–5896, Long Beach, CA, 2019.

[44] David Speck, André Biedenkapp, Frank Hutter, Robert Mattmüller, and Marius Lindauer. Learning heuristic selection with dynamic algorithm configuration. In *Proceedings of the 31th International Conference on Automated Planning and Scheduling*, pages 597–605, Guangzhou, China, 2021.

[45] Jianyong Sun, Xin Liu, Thomas Bäck, and Zongben Xu. Learning adaptive differential evolution algorithm from optimization experiences by policy gradient. *IEEE Transactions on Evolutionary Computation*, 25(4):666–680, 2021.

[46] Peter Sunehag, Guy Lever, Audrunas Gruslys, Wojciech Marian Czarnecki, Vinícius Flores Zambaldi, Max Jaderberg, Marc Lanctot, Nicolas Sonnerat, Joel Z. Leibo, Karl Tuyls, and Thore Graepel. Value-decomposition networks for cooperative multi-agent learning based on team reward. In *Proceedings of the 17th International Conference on Autonomous Agents and MultiAgent Systems*, pages 2085–2087, Stockholm, Sweden, 2018.

[47] Ardi Tampuu, Tambet Matiisen, Dorian Kodelja, Ilya Kuzovkin, Kristjan Korjus, Juhan Aru, Jaan Aru, and Raul Vicente. Multiagent cooperation and competition with deep reinforcement learning. *PloS one*, 12(4):e0172395, 2017.

[48] Justin K. Terry, Benjamin Black, Nathaniel Grammel, Mario Jayakumar, Ananth Hari, Ryan Sullivan, Luis S. Santos, Clemens Dieffendahl, Caroline Horsch, Rodrigo Perez-Vicente, Niall L. Williams, Yashas Lokesh, and Praveen Ravi. Pettingzoo: Gym for multi-agent reinforcement learning. In *Advances in Neural Information Processing Systems 34*, pages 15032–15043, Virtual, 2021.

[49] Ye Tian, Ran Cheng, Xingyi Zhang, and Yaochu Jin. PlatEMO: A MATLAB platform for evolutionary multi-objective optimization. *IEEE Computational Intelligence Magazine*, 12(4): 73–87, 2017.

[50] Ye Tian, Xiaopeng Li, Haiping Ma, Xingyi Zhang, Kay Chen Tan, and Yaochu Jin. Deep reinforcement learning based adaptive operator selection for evolutionary multi-objective optimization. *IEEE Transactions on Emerging Topics in Computational Intelligence*, in press.

[51] Anupam Trivedi, Dipti Srinivasan, Krishnendu Sanyal, and Abhiroop Ghosh. A survey of multiobjective evolutionary algorithms based on decomposition. *IEEE Transactions on Evolutionary Computation*, 21(3):440–462, 2017.

[52] Ceyer Wakilpoor, Patrick J Martin, Carrie Rebhuhn, and Amanda Vu. Heterogeneous multi-agent reinforcement learning for unknown environment mapping. *arXiv preprint arXiv:2010.02663*, 2020.

[53] Jianhong Wang, Wangkun Xu, Yunjie Gu, Wenbin Song, and Tim C. Green. Multi-agent reinforcement learning for active voltage control on power distribution networks. In *Advances in Neural Information Processing Systems 34*, pages 3271–3284, Virtual, 2021.

[54] Zhenkun Wang, Qingfu Zhang, Aimin Zhou, Maoguo Gong, and Licheng Jiao. Adaptive replacement strategies for MOEA/D. *IEEE Transactions on Cybernetics*, 46(2):474–486, 2016.

[55] Jiayi Weng, Huayu Chen, Dong Yan, Kaichao You, Alexis Duburcq, Minghao Zhang, Hang Su, and Jun Zhu. Tianshou: A highly modularized deep reinforcement learning library. *arXiv preprint arXiv:2107.14171*, 2021.

[56] Yaodong Yang and Jun Wang. An overview of multi-agent reinforcement learning from game theoretical perspective. *arXiv preprint arXiv:2011.00583*, 2020.

[57] Lei Yuan, Chenghe Wang, Jianhao Wang, Fuxiang Zhang, Feng Chen, Cong Guan, Zongzhang Zhang, Chongjie Zhang, and Yang Yu. Multi-agent concentrative coordination with decentralized task representation. In *Proceedings of the 31st International Joint Conference on Artificial Intelligence*, pages 599–605, Vienna, Austria, 2022.

[58] Kaiqing Zhang, Zhuoran Yang, and Tamer Başar. Multi-agent reinforcement learning: A selective overview of theories and algorithms. *Handbook of Reinforcement Learning and Control*, pages 321–384, 2021.

[59] Qingfu Zhang and Hui Li. MOEA/D: A multiobjective evolutionary algorithm based on decomposition. *IEEE Transactions on Evolutionary Computation*, 11(6):712–731, 2007.

[60] Lianmin Zheng, Jiacheng Yang, Han Cai, Ming Zhou, Weinan Zhang, Jun Wang, and Yong Yu. Magent: A many-agent reinforcement learning platform for artificial collective intelligence. In *Proceedings of the 32th AAAI Conference on Artificial Intelligence*, pages 8222–8223, New Orleans, LA, 2018.

[61] Eckart Zitzler and Lothar Thiele. Multiobjective optimization using evolutionary algorithms - A comparative case study. In *Proceedings of the 5th International Conference on Parallel Problem Solving from Nature*, pages 292–304, Amsterdam, The Netherlands, 1998.

Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes] See Abstract and Section1.
   (b) Did you describe the limitations of your work? [Yes] We describe the limitations in Section 6.
   (c) Did you discuss any potential negative societal impacts of your work? [Yes] The authors do not see obvious negative societal impacts of the proposed method
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes] Our paper conforms to them.
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [N/A]
   (b) Did you include complete proofs of all theoretical results? [N/A]
3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] Yes, see Section 5, Appendix and Supplementary material.
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] Yes, see Section 5 and Appendix.
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes] Yes, see Section 5 and Appendix.
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes] Yes, see Appendix.
4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes] See References.
   (b) Did you mention the license of the assets? [N/A]
   (c) Did you include any new assets either in the supplemental material or as a URL? [Yes] See supplemental material.
   (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [N/A]
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [N/A]
5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]

A Details of MA-DAC

A.1 Details of MOEA/D

First, we give a brief introduction to multi-objective optimization problems (MOPs), which can be defined as

$$\min \ \boldsymbol{F}(\boldsymbol{x}) = (f_1(\boldsymbol{x}), \ldots, f_m(\boldsymbol{x})) \quad \text{s.t.} \quad \boldsymbol{x} \in \Omega, \tag{5}$$

where $\boldsymbol{x} = (x_1, \ldots, x_D)$ is a solution, $\boldsymbol{F} : \Omega \to \mathbb{R}^m$ constitutes m objective functions, $\Omega = [x_i^L, x_i^U]^D \subseteq \mathbb{R}^D$ is the solution space, and $\mathbb{R}^m$ is the objective space.

Definition A.1. A solution $\boldsymbol{x}^*$ is Pareto-optimal with respect to Eq. (5), if $\nexists \boldsymbol{x} \in \Omega$ such that $\forall i : f_i(\boldsymbol{x}) \leq f_i(\boldsymbol{x}^*)$ and $\exists i : f_i(\boldsymbol{x}) < f_i(\boldsymbol{x}^*)$. The set of all Pareto-optimal solutions is called Pareto-optimal set (PS). The set of the corresponding objective vectors of PS, i.e., $\{\boldsymbol{F}(\boldsymbol{x}) \mid \boldsymbol{x} \in \text{PS}\}$, is called Pareto front (PF).

Instead of focusing on a single optimal solution in single-objective optimization, the goal of MOP is to find at least one Pareto-optimal solution for each objective vector in the PF. However, as the size of PF can be prohibitively large or even infinite, it is often to find a set of solutions that can approximate the PS well, i.e., the set of their objective vectors can approximate the PF well.

Evolutionary algorithms have demonstrated their effectiveness in solving MOPs. Their population-based nature can approximate the Pareto optimal solutions within one execution, with each solution in the population representing a unique trade-off among the objectives. MOEA/D [59] is a representative multi-objective evolutionary algorithm. MOEA/D converts an MOP into a number of single-objective sub-problems through a number of weights, where neighboring solutions work cooperatively for the optimal solutions for the single-objective sub-problems. Note that an optimal solution for a single-objective sub-problem must be Pareto optimal for the MOP.

MOEA/D consists of two major processes, i.e., *decomposition* and *collaboration* [59, 51, 25]. In decomposition, MOEA/D transforms the task of approximating the PF into a number of sub-problems through a number of weights and an aggregation function. There have been several aggregation functions for MOEA/D. Here, we introduce the common Tchebycheff approach (TCH) that is also used in this paper. Given a weight vector $\boldsymbol{w} = (w_1, \ldots, w_m)$ where $w_i \geq 0, \forall i \in \{1, \ldots, m\}$ and $\sum_{i=1}^m w_i = 1$, the sub-problem by TCH is formulated as

$$\min_{\boldsymbol{x} \in \Omega} \ g(\boldsymbol{x} \mid \boldsymbol{w}, \boldsymbol{z}^*) = \max_{1 \leq i \leq m} \{w_i \cdot |f_i(\boldsymbol{x}) - z_i^*|\}, \tag{6}$$

where $\boldsymbol{z}^* = (z_1^*, \ldots, z_m^*)$ is the ideal point consisting of the best objective values obtained so far.

The basic idea of collaboration is that neighboring sub-problems are more likely to share similar properties, e.g., similar objective functions and/or optimal solutions [25]. In particular, the neighborhood of a sub-problem is determined by the Euclidean distance of its corresponding weight vector with respect to the others and the hyperparameter *neighborhood size*: if the distance between two sub-problems is smaller than the neighborhood size, they are the neighborhood of each other. In the mating selection of a sub-problem, the parent solutions are randomly selected from its neighborhood, and the newly generated offspring solution is used to update the solutions of sub-problems within the same neighborhood.

The procedure of MOEA/D used in this paper is described in Algorithm 1. Firstly, it generates a population $\{\boldsymbol{x}^{(i)}\}_{i=1}^N$ of solutions with size N, associated with N weight vectors $\{\boldsymbol{w}^{(i)}\}_{i=1}^N$ in line 1. A weight vector $\boldsymbol{w}^{(i)}$ corresponds to a single-objective sub-problem, and $\boldsymbol{x}^{(i)}$ is the current best solution associated with this sub-problem. Then, in each iteration (i.e., lines 4–10) of MOEA/D, for each sub-problem, it selects parent solutions from the neighborhood, generates an offspring solution by reproduction operators, and updates the solutions of the sub-problem and its neighboring sub-problem(s). After obtaining parent solutions in line 5, it uses crossover operators (e.g., simulated binary crossover (SBX) operator or differential evolution (DE) operator) and polynomial mutation (PM) operator [59], to generate an offspring solution $\boldsymbol{x}'^{(i)}$ in line 6. Then, it evaluates the offspring solution and obtain the objective vector $\boldsymbol{F}(\boldsymbol{x}'^{(i)})$ in line 7. Finally, it uses the offspring solution to update the ideal point $\boldsymbol{z}^*$ in line 8 and the solutions of the sub-problems within the neighborhood $\Theta^{\boldsymbol{w}^{(i)}}$ of the current sub-problem $\boldsymbol{w}^{(i)}$ in line 9. For each $j \in \{1, 2, \ldots, m\}$, z_j^* is the best found value of the j-th objective f_j, and thus if $f_j(\boldsymbol{x}'^{(i)})$ is better, i.e., $f_j(\boldsymbol{x}'^{(i)}) < z_j^*$, then z_j^* will be

Algorithm 1: MOEA/D

```
Parameters: Population size $N$, number $T$ of iterations
1  Initialize a population $\{\boldsymbol{x}^{(i)}\}_{i=1}^N$ of solutions, and a corresponding set $W = \{\boldsymbol{w}^{(i)}\}_{i=1}^N$ of weight vectors ;
2  $t = 0$ ;
3  while $t < T$ do
4      for $i = 1 : N$ do
5          Randomly select parent solutions from the neighborhood of $\boldsymbol{w}^{(i)}$ , denoted as $\Theta^{\boldsymbol{w}^{(i)}}$ ;
6          Use crossover and mutation operators to generate an offspring solution $\boldsymbol{x}'^{(i)}$;
7          Evaluate the offspring solution to obtain $\boldsymbol{F}(\boldsymbol{x}'^{(i)})$;
8          Update the ideal point $\boldsymbol{z}^*$. That is, for any $j \in \{1, 2, \ldots, m\}$, if $f_j(\boldsymbol{x}'^{(i)}) < \boldsymbol{z}_j^*$, then $\boldsymbol{z}_j^* = f_j(\boldsymbol{x}'^{(i)})$;
9          Update the corresponding solution of each sub-problem within $\Theta^{\boldsymbol{w}^{(i)}}$ by $\boldsymbol{x}'^{(i)}$. That is, for each $\boldsymbol{w}^{(j)} \in \Theta^{\boldsymbol{w}^{(i)}}$, if $g(\boldsymbol{x}'^{(i)} \mid \boldsymbol{w}^{(j)}, \boldsymbol{z}^*) < g(\boldsymbol{x}^{(j)} \mid \boldsymbol{w}^{(j)}, \boldsymbol{z}^*)$, then $\boldsymbol{x}^{(j)} = \boldsymbol{x}'^{(i)}$
10     end
11     $t = t + 1$
12 end
```

udpated accordingly. For each sub-problem $\boldsymbol{w}^{(j)}$ within $\Theta^{\boldsymbol{w}^{(i)}}$, if $\boldsymbol{x}'^{(i)}$ is better than its corresponding solution $\boldsymbol{x}^{(j)}$, i.e., $g(\boldsymbol{x}'^{(i)} \mid \boldsymbol{w}^{(j)}, \boldsymbol{z}^*) < g(\boldsymbol{x}^{(j)} \mid \boldsymbol{w}^{(j)}, \boldsymbol{z}^*)$, then $\boldsymbol{x}^{(j)}$ will be udpated accordingly.

A.2 State formulation

The state of our proposed benchmark, i.e., MaMo, can be divided into three parts.

1. To describe the general properties of the optimization problems, the first part (i.e., indexes 0–1 in Table 5) contains the features of the problem instance, i.e., the numbers of objectives and variables.
2. To emphasize the general information of the algorithm, the second part (i.e., indexes 2–3 in Table 5) contains the features of the optimization process, i.e., how much computational budget has been used and how many steps of the algorithm have not made any progress, i.e., stagnant count ratio.
3. To show the properties of the population and that how the population is evolved, we use several indicators, i.e., hypervolume [61], ratio of non-dominated solutions in the population, and average distance of the solutions [27] in the third part (i.e., indexes 4–21 in Table 5). For each indicator, we also use the gap between the current value and the value corresponding to the last population to reflect the immediate evolutionary progress. Besides, we use statistic metrics (i.e., the mean and standard deviation) of these indicators in the last five steps and all steps from the beginning to characterize the short and long histories of the optimization, respectively.

The detailed state features at step t are shown in Table 5. We use $\mathrm{List}(I, t, l)$ to denote a list of indicator values from step $t - l + 1$ to t, i.e., $[I_{t-l+1}, \ldots, I_t]$, where I denotes a specific indicator and I_i denotes the indicator value at step i. Note that $\forall i < 0, I_i = 0$ as default. For the considered three indicators, i.e., hypervolume, ratio of non-dominated solutions in the population and average distance of the solutions, they are denoted as HV, $\mathrm{NDRatio}$ and Dist, respectively.

To facilitate the generalization of the learned MA-DAC policy, we pre-process some state features to make them in $[-1, 1]$. For state features 0 and 1, we use $1/m$ and $1/D$, respectively, where m is the number of objectives and D is the number of variables. They apparently belong to $[0, 1]$. For state features 2, 3, 4 and 5, they are defined in $[0, 1]$. State feature 6 is the average distance between the solutions in the population. We sample a sufficient number of solutions before optimization, and calculate the maximum distance between them, which is used as a scaling denominator when calculating state feature 6. State features 7-9 are the difference of two values in $[0, 1]$, and thus belong

Table 5: State at step t in MaMo.

Index	Parts of state	Feature	Notes
0	1	$1/m$	m: Number of objectives
1	1	$1/D$	D: Number of variables
2	2	t/T	Computational budget that has been used
3	2	N_{stag}/T	Stagnant count ratio
4	3	HV_t	Hypervolume value
5	3	NDRatio_t	Ratio of non-dominated solutions
6	3	Dist_t	Average distance
7	3	$\text{HV}_t - \text{HV}_{t-1}$	Change of HV between steps t and $t-1$
8	3	$\text{NDRatio}_t - \text{NDRatio}_{t-1}$	Change of NDRatio between steps t and $t-1$
9	3	$\text{Dist}_t - \text{Dist}_{t-1}$	Change of Dist between steps t and $t-1$
10	3	$\text{Mean}(\text{List}(\text{HV}, t, 5))$	Mean of HV in the last 5 steps
11	3	$\text{Mean}(\text{List}(\text{NDRatio}, t, 5))$	Mean of NDRatio in the last 5 steps
12	3	$\text{Mean}(\text{List}(\text{Dist}, t, 5))$	Mean of Dist in the last 5 steps
13	3	$\text{Std}(\text{List}(\text{HV}, t, 5))$	Standard deviation of HV in the last 5 steps
14	3	$\text{Std}(\text{List}(\text{NDRatio}, t, 5))$	Standard deviation of NDRatio in the last 5 steps
15	3	$\text{Std}(\text{List}(\text{Dist}, t, 5))$	Standard deviation of Dist in the last 5 steps
16	3	$\text{Mean}(\text{List}(\text{HV}, t, t))$	Mean of HV in all the steps so far
17	3	$\text{Mean}(\text{List}(\text{NDRatio}, t, t))$	Mean of NDRatio in all the steps so far
18	3	$\text{Mean}(\text{List}(\text{Dist}, t, t))$	Mean of Dist in all the steps so far
19	3	$\text{Std}(\text{List}(\text{HV}, t, t))$	Standard deviation of HV in all the steps so far
20	3	$\text{Std}(\text{List}(\text{NDRatio}, t, t))$	Standard deviation of NDRatio in all the steps so far
21	3	$\text{Std}(\text{List}(\text{Dist}, t, t))$	Standard deviation of Dist in all the steps so far

to $[-1, 1]$. For state features 10-21, they are statistical values (i.e., mean and standard deviation) of state features 4-6.

A.3 Action formulation

We consider four heterogeneous types of configuration hyperparameters in MOEA/D as the actions of four different agents of MA-DAC.

Weights. In MOEA/D, weights are used to transform an MOP into multiple single-objective sub-problems, which should be as diverse as possible [59]. Inspired by MOEA/D-AWA [37], the action space for weights is discrete with two dimensions, i.e., adjusting (T) and not adjusting (N) the weights. Furthermore, we limit the frequency of adjustment because too frequent adjustment will lead to drastic changes in the sub-problems and is detrimental to the optimization process [37]. If the action is T, weights will be updated before selecting the parent solutions. The weights adaptation mechanism is as follows.

We first calculate the sparsity level of each solution $\boldsymbol{x}^{(i)}$ based on vicinity distance [24]:

$$SL\left(\boldsymbol{x}^{(i)}, \{\boldsymbol{x}^{(p)}\}_{p=1}^{N}\right) = \prod_{j=1}^{m} l(\boldsymbol{x}^{(i)}, j), \tag{7}$$

where $l(\boldsymbol{x}^{(i)}, j)$ is the Euclidean distance between $\boldsymbol{x}^{(i)}$ and its j-th nearest neighbor in the population $\{\boldsymbol{x}^{(p)}\}_{p=1}^{N}$. The m closest neighbors in the population are used for calculation, where m is the number of objectives. After calculating the sparsity level of each solution, the sub-problems corresponding to the solutions whose sparsity levels are ranked bottom 5%, i.e., the overcrowded solutions, will be removed.

To ensure that there are still N sub-problems in total, we should add $0.05N$ new sub-problems and their corresponding solutions. The newly added solutions are from an elite population, which stores all historical non-dominated solutions with a capacity of $1.5N$. If the size of the elite population exceeds the capacity, the solutions with the lowest sparsity level will be removed. For each solution $\boldsymbol{x}'$ in the elite population, we calculate its sparsity level with respect to the current population, i.e., $SL(\boldsymbol{x}', \text{Pop})$, where Pop denotes the set of $0.95N$ solutions in the current population after removing the overcrowded solutions. Then, we select the solution from the elite population, which has the highest sparsity level with respect to the current population, and add it to the current population; this process is repeated for $0.05N$ times. For each newly added solution, the corresponding sub-problem (i.e., weight vector) is generated in a specific way, whose details can refer to Algorithm 3 in [37].

Neighborhood size. The neighborhood size is to control the distance between solutions in mating selection. A small size helps the search exploit the local area, while a large size helps the search explore a wide objective space [54]. We discretize the action space into four dimensions, i.e., 15, 20, 25 and 30, where 20 is the default value.

Types of reproduction operators. We consider four types of DE operators with different search abilities introduced in [26]. Assuming that we are reproducing an offspring solution for the i-th sub-problem. Let $\boldsymbol{x}^{(i)}$ and $\boldsymbol{x}'^{(i)}$ denote its current solution and the generated offspring solution, respectively. The equations of four types of DE operators are shown as follows:

- OP1: $\boldsymbol{x}'^{(i)} = \boldsymbol{x}^{(i)} + F \times \left(\boldsymbol{x}^{(r_1)} - \boldsymbol{x}^{(r_2)}\right)$,
- OP2: $\boldsymbol{x}'^{(i)} = \boldsymbol{x}^{(i)} + F \times \left(\boldsymbol{x}^{(r_1)} - \boldsymbol{x}^{(r_2)}\right) + F \times \left(\boldsymbol{x}^{(r_3)} - \boldsymbol{x}^{(r_4)}\right)$,
- OP3: $\boldsymbol{x}'^{(i)} = \boldsymbol{x}^{(i)} + K \times \left(\boldsymbol{x}^{(i)} - \boldsymbol{x}^{(r_1)}\right) + F \times \left(\boldsymbol{x}^{(r_2)} - \boldsymbol{x}^{(r_3)}\right) + F \times \left(\boldsymbol{x}^{(r_4)} - \boldsymbol{x}^{(r_5)}\right)$,
- OP4: $\boldsymbol{x}'^{(i)} = \boldsymbol{x}^{(i)} + K \times \left(\boldsymbol{x}^{(i)} - \boldsymbol{x}^{(r_1)}\right) + F \times \left(\boldsymbol{x}^{(r_2)} - \boldsymbol{x}^{(r_3)}\right)$.

Here, $\boldsymbol{x}^{(r_1)}, \boldsymbol{x}^{(r_2)}, \boldsymbol{x}^{(r_3)}, \boldsymbol{x}^{(r_4)}$, and $\boldsymbol{x}^{(r_5)}$ are different parent solutions randomly selected from the neighborhood of $\boldsymbol{x}^{(i)}$. The scaling factor $F > 0$ controls the impact of the vector differences on the mutant vector, and $K \in [0, 1]$ plays a similar role to F.

Parameters of reproduction operators. The parameters (e.g., scaling factor) of the reproduction operators in MOEA/D significantly affect the algorithm's performance [45]. We set the scaling factor K to a fixed value of 0.5 as recommended [26], and dynamically adjust the scaling factor F. The action space has four discrete dimensions, i.e., 0.4, 0.5, 0.6 and 0.7, where 0.5 is the default value.

B Additional results on MaMo

B.1 Details of experimental settings

Common settings of MOEA/D We implement MOEA/D with `Platypus`.[3] All algorithms mentioned in this paper use the same common settings [59, 50], as shown in Table 6.

Table 6: Common Settings of MOEA/D.

General settings	
Population size N	210
Number T of iterations	$100 \times m$
Reproduction operators	
Crossover operator	Simulated binary crossover (SBX)
Distribution index of SBX	20
Mutation operator	Polynomial mutation (PM)
Probability of PM	$1/D$
Distribution index of PM	20
Aggregation function	
Aggregation function	Tchebycheff approach
Neighborhood size	20

[3] `https://github.com/Project-Platypus/Platypus`

DQN We implement DQN with the `tianshou`[4] [55] framework and adjust some of the hyperparameters to fit this new task. The network structure is:

$$\text{state} \rightarrow \textbf{MLP}(128) \rightarrow \textbf{relu} \rightarrow \textbf{MLP}(128) \rightarrow \textbf{relu} \rightarrow \textbf{MLP}(128) \rightarrow \textbf{relu} \rightarrow \textbf{MLP}(\text{number of actions})$$

where $\textbf{MLP}(n)$ means a fully-connected layer with output size of n, and **relu** means Rectified Linear Units. Here, the action apace is the concatenation of the four types of configuration hyperparameters, with a dimension of 128 (i.e., $4 \times 4 \times 4 \times 2$). Some key hyperparameters of DQN are as follows:

- The learning rate is $3e$-4.
- The discounting factor γ is 0.99.
- The buffer size is $50,000$ (where unit is transition).
- The number of training steps is $400,000$.

MA-UCB MA-UCB uses four upper confidence bound (UCB) [2] agents to adjust the four types of hyperparameters [17]. Each agent follows the UCB action selection rule, i.e., the action taken by agent i at step t is

$$a_t^{(i)} \doteq \arg\max_{a^{(i)}} \left[Q_t(a^{(i)}) + c\sqrt{\frac{\ln t}{N_t(a^{(i)})}} \right], \tag{8}$$

where $Q_t(a^{(i)})$ denotes the estimated value of $a^{(i)}$ at step t, $N_t(a^{(i)})$ denotes the number of times that action $a^{(i)}$ has been selected at step t, and the number $c > 0$ (the value is 1.0 here) controls the degree of exploration.

MOEA/D-FRRMAB We modify the implementation of FRRMAB from the `PlatEMO`[5] [49] framework to make a fair comparison. That is, the original adaptive operator selection mechanism and related hyperparameters are retained, except that it uses the same settings of MOEA/D as MA-DAC. MOEA/D-FRRMAB adjusts the four types of DE operators by MAB. In particular, we searched for some sensitive hyperparameters according to the suggestions in [26], and the best performing combination is shown as follows:

- Scaling factor is 2.0.
- Size of the sliding window is $0.5 \times N$.
- Decaying factor is 0.3.

MOEA/D-AWA We modify the implementation of MOEA/D-AWA from the `PlatEMO` framework to make a fair comparison. That is, the original adaptive weight vector adjustment strategy and related hyperparameters are retained, except that it uses the same settings of MOEA/D as MA-DAC.

MA-DAC We use the default VDN policy network without parameter sharing in the `EPyMARL`[6] [36] framework. MA-DAC and all its variants use the same hyperparameters. Some key hyperparameters are as follows:

- The learning rate is $1e$-4.
- The discounting factor γ is 0.99.
- The buffer size is $5,000$ (where unit is episode).
- The number of training steps is $400,000$.

All hyperparameters of the above algorithms can be found in the code.

Computing resources The experiments are conducted on six PCs with an AMD Ryzen 9 3950X 16-Core Processor and an NVIDIA GeForce RTX 3090 GPU.

[4]`https://github.com/thu-ml/tianshou`
[5]`https://github.com/BIMK/PlatEMO`
[6]`https://github.com/uoe-agents/epymarl`

B.2 Analysis of the reward function

In this subsection, we compare our proposed reward function with the three types of reward functions proposed by [42], as shown in the following:

$$r_t^1 = \max\{f(s_t) - f(s_{t+1}), 0\}, \tag{9}$$

$$r_t^2 = \begin{cases} 10 & \text{if } f(s_{t+1}) < f_t^* \\ 1 & \text{else if } f(s_{t+1}) < f(s_t) \\ 0 & \text{otherwise} \end{cases}, \tag{10}$$

$$r_t^3 = \max\left\{\frac{f(s_t) - f(s_{t+1})}{f(s_{t+1}) - f_{\text{opt}}}, 0\right\}, \tag{11}$$

where $f(s_t)$ is the metric value at step t, f_t^* is the minimum metric value achieved until step t, and f_{opt} is the optimal metric value, i.e., the global minimum value. Here, we use IGD [6] as the metric $f(\cdot)$, and thus $f_{\text{opt}} = 0$. We train MA-DAC policy with these three reward functions r_t^1, r_t^2 and r_t^3, which are denoted as MA-DAC-R1, MA-DAC-R2 and MA-DAC-R3, respectively.

The experimental results are shown in Table 7. We can see that MA-DAC has the best average rank, indicating the effectiveness of our proposed reward function. For the other three methods, MA-DAC-R2 and MA-DAC-R3 are better than MA-DAC-R1, which is consistent with the observation in [42].

Table 7: IGD values obtained by MA-DAC-R1, MA-DAC-R2, MA-DAC-R3 and MA-DAC on different problems. Each result consists of the mean and standard deviation of 30 runs. The best mean value on each problem is highlighted in **bold**. The symbols '$+$', '$-$' and '$\approx$' indicate that the result is significantly superior to, inferior to, and almost equivalent to MA-DAC, respectively, according to the Wilcoxon rank-sum test with significance level 0.05.

Problem	M	MA-DAC-R1	MA-DAC-R2	MA-DAC-R3	MA-DAC
DTLZ2	3	4.223E-02 (2.50E-03) $-$	3.853E-02 (5.58E-04) $-$	3.809E-02 (4.64E-04) $\approx$	**3.807E-02** (5.05E-04)
	5	2.401E-01 (8.27E-03) $-$	2.726E-01 (1.51E-02) $\approx$	**2.364E-01** (1.04E-02) $+$	2.442E-01 (1.26E-02)
	7	4.142E-01 (1.12E-02) $-$	4.248E-01 (1.30E-02) $-$	4.215E-01 (9.03E-03) $-$	**3.944E-01** (1.17E-02)
WFG4	3	5.989E-02 (5.60E-03) $\approx$	5.255E-02 (1.14E-03) $-$	5.309E-02 (8.02E-04) $-$	**5.200E-02** (1.19E-03)
	5	1.848E-01 (2.61E-03) $+$	1.851E-01 (2.43E-03) $+$	**1.846E-01** (2.20E-03) $+$	1.868E-01 (2.81E-03)
	7	3.028E-01 (3.19E-03) $+$	**3.008E-01** (3.51E-03) $\approx$	3.029E-01 (3.36E-03) $\approx$	3.033E-01 (3.66E-03)
WFG6	3	7.920E-02 (1.81E-02) $+$	4.909E-02 (1.50E-02) $-$	**4.814E-02** (1.22E-02) $\approx$	4.831E-02 (8.95E-03)
	5	1.977E-01 (6.17E-03) $-$	2.037E-01 (4.49E-03) $-$	1.975E-01 (5.78E-03) $-$	**1.942E-01** (6.90E-03)
	7	**3.110E-01** (4.86E-03) $-$	3.151E-01 (5.01E-03) $\approx$	3.148E-01 (4.05E-03) $-$	3.112E-01 (4.93E-03)
Train: average rank		2.67	3.11	2.11	2.11
Train: $+/-/\approx$		3/5/1	1/5/3	2/4/3	
DTLZ4	3	**5.567E-02** (7.33E-03) $-$	7.236E-02 (6.19E-02) $-$	6.144E-02 (5.10E-02) $\approx$	6.700E-02 (6.14E-02)
	5	3.119E-01 (1.91E-02) $-$	3.221E-01 (2.12E-02) $-$	3.119E-01 (1.58E-02) $-$	**2.995E-01** (2.10E-02)
	7	4.354E-01 (1.29E-02) $-$	4.385E-01 (1.23E-02) $-$	4.275E-01 (1.60E-02) $-$	**4.182E-01** (1.21E-02)
WFG5	3	4.841E-02 (7.78E-04) $-$	4.763E-02 (7.73E-04) $-$	4.773E-02 (6.58E-04) $-$	**4.730E-02** (7.89E-04)
	5	1.823E-01 (2.49E-03) $\approx$	1.818E-01 (2.90E-03) $-$	1.812E-01 (3.06E-03) $\approx$	**1.811E-01** (3.02E-03)
	7	3.212E-01 (6.60E-03) $\approx$	**3.174E-01** (6.43E-03) $\approx$	3.196E-01 (5.99E-03) $\approx$	3.206E-01 (8.04E-03)
WFG7	3	4.555E-02 (1.26E-03) $\approx$	4.076E-02 (5.41E-04) $-$	4.168E-02 (6.40E-04) $-$	**4.066E-02** (5.31E-04)
	5	1.842E-01 (3.28E-03) $\approx$	1.865E-01 (2.93E-03) $+$	**1.841E-01** (3.95E-03) $+$	1.858E-01 (2.12E-03)
	7	3.335E-01 (1.09E-02) $+$	**3.199E-01** (9.86E-03) $-$	3.271E-01 (9.65E-03) $\approx$	3.258E-01 (1.25E-02)
WFG8	3	8.914E-02 (2.96E-03) $\approx$	7.911E-02 (1.06E-03) $-$	8.199E-02 (1.96E-03) $-$	**7.901E-02** (1.19E-03)
	5	2.551E-01 (1.02E-02) $-$	2.628E-01 (1.22E-02) $-$	2.541E-01 (9.08E-03) $-$	**2.479E-01** (7.20E-03)
	7	4.163E-01 (9.54E-03) $\approx$	**4.115E-01** (9.80E-03) $\approx$	4.197E-01 (7.52E-03) $-$	4.127E-01 (5.93E-03)
WFG9	3	5.003E-02 (9.00E-03) $-$	4.208E-02 (6.56E-04) $-$	4.428E-02 (9.97E-03) $-$	**4.159E-02** (6.10E-04)
	5	1.929E-01 (8.84E-03) $\approx$	**1.819E-01** (5.73E-03) $-$	1.951E-01 (9.83E-03) $-$	1.832E-01 (7.10E-03)
	7	3.342E-01 (8.56E-03) $-$	3.322E-01 (8.89E-03) $-$	3.327E-01 (8.02E-03) $-$	**3.278E-01** (7.21E-03)
Test: average rank		3.27	2.47	2.67	1.60
Test: $+/-/\approx$		1/7/7	1/12/2	1/10/4	

B.3 Analysis of the reproduction operators

In this subsection, we give a detailed analysis of the reproduction operators, including the four types of DE operators introduced in Appendix A.3, and also further compare MA-DAC with MOEA/D-FRRMAB, which applies the MAB-based adaptive tuning method FRRMAB [26] to dynamically adjust the types of DE operators used in MOEA/D.

First, we examine the performance of MOEA/D equipped with each type of DE operator, where the DE operator is used as the crossover operator with a default scaling factor $F = 0.5$. The results are shown in Table 8. Compared with the original MOEA/D using the SBX operator, these methods using the DE operator achieve a similar performance, as the numbers of '$+$' and '$-$' are close. Among the methods using the DE operator, MOEA/D-OP2 has the best average rank, which has thus also been used as the default DE operator in MA-DAC (M) w/o 3. Note that MA-DAC (M) w/o 3 denotes MA-DAC (M) without tuning the types of reproduction operators, which is used to validate the effectiveness of adjusting all configuration hyperparameters simultaneously in RQ3 of the main paper.

Table 8: IGD values obtained by MOEA/D-OP1, MOEA/D-OP2, MOEA/D-OP3 and MOEA/D-OP4 on different problems. Each result consists of the mean and standard deviation of 30 runs. The best mean value on each problem is highlighted in **bold**. The symbols '$+$', '$-$' and '$\approx$' indicate that the result is significantly superior to, inferior to, and almost equivalent to the original MOEA/D (i.e., the column MOEA/D in Table 2 of the main paper or Table 9), respectively, according to the Wilcoxon rank-sum test with significance level 0.05.

Problem	M	MOEA/D-OP1	MOEA/D-OP2	MOEA/D-OP3	MOEA/D-OP4
DTLZ2	3	**4.681E-02** (2.95E-04) $-$	4.691E-02 (3.97E-04) $-$	6.050E-02 (2.64E-03) $-$	5.033E-02 (1.07E-03) $-$
	5	3.037E-01 (9.85E-04) $-$	**3.012E-01** (1.51E-03) $\approx$	3.391E-01 (1.06E-02) $-$	3.083E-01 (2.69E-03) $-$
	7	4.735E-01 (9.68E-03) $-$	**4.551E-01** (4.43E-03) $-$	4.988E-01 (1.01E-02) $-$	4.887E-01 (9.51E-03) $-$
WFG4	3	**6.934E-02** (1.54E-03) $-$	7.293E-02 (1.43E-03) $-$	9.046E-02 (4.01E-03) $-$	7.998E-02 (2.25E-03) $-$
	5	2.930E-01 (1.03E-02) $+$	2.761E-01 (6.39E-03) $+$	2.762E-01 (5.86E-03) $+$	**2.761E-01** (7.63E-03) $+$
	7	4.057E-01 (1.45E-02) $+$	3.711E-01 (9.79E-03) $+$	**3.617E-01** (6.46E-03) $+$	3.696E-01 (1.06E-02) $+$
WFG6	3	7.470E-02 (2.22E-02) $+$	**6.714E-02** (1.59E-02) $+$	7.665E-02 (9.41E-03) $-$	9.557E-02 (1.71E-02) $-$
	5	3.513E-01 (1.46E-02) $+$	3.285E-01 (2.33E-02) $+$	**3.254E-01** (1.39E-02) $+$	3.421E-01 (1.30E-02) $+$
	7	4.918E-01 (3.31E-02) $\approx$	4.797E-01 (3.04E-02) $\approx$	**4.328E-01** (2.81E-02) $+$	4.478E-01 (3.08E-02) $+$
DTLZ4	3	7.897E-02 (6.36E-02) $-$	**6.226E-02** (4.05E-03) $-$	1.296E-01 (1.23E-02) $-$	7.890E-02 (9.62E-03) $-$
	5	3.504E-01 (2.77E-02) $-$	**3.413E-01** (1.48E-02) $-$	3.631E-01 (7.24E-03) $-$	3.521E-01 (1.23E-02) $-$
	7	4.923E-01 (1.89E-02) $-$	**4.519E-01** (1.15E-02) $-$	4.766E-01 (1.35E-02) $-$	4.975E-01 (2.23E-02) $-$
WFG5	3	6.181E-02 (5.85E-04) $+$	6.177E-02 (8.01E-04) $+$	6.128E-02 (5.59E-04) $+$	**6.113E-02** (5.30E-04) $+$
	5	3.138E-01 (6.20E-03) $+$	3.052E-01 (7.19E-03) $+$	**3.031E-01** (7.37E-03) $+$	3.116E-01 (8.26E-03) $+$
	7	**4.945E-01** (1.24E-02) $-$	4.988E-01 (1.04E-02) $-$	5.197E-01 (1.01E-02) $-$	5.189E-01 (1.22E-02) $-$
WFG7	3	**5.929E-02** (6.35E-04) $-$	6.033E-02 (8.84E-04) $-$	8.382E-02 (4.86E-03) $-$	6.699E-02 (1.75E-03) $-$
	5	3.286E-01 (1.55E-02) $+$	2.941E-01 (9.66E-03) $+$	**2.924E-01** (1.12E-02) $+$	3.148E-01 (1.58E-02) $+$
	7	5.062E-01 (2.46E-02) $+$	4.739E-01 (2.51E-02) $+$	**4.479E-01** (2.28E-02) $+$	4.859E-01 (2.72E-02) $+$
WFG8	3	**9.314E-02** (9.12E-04) $-$	9.598E-02 (1.22E-03) $-$	1.213E-01 (3.36E-03) $-$	1.070E-01 (2.16E-03) $-$
	5	4.112E-01 (1.14E-02) $+$	3.884E-01 (1.19E-02) $+$	**3.808E-01** (7.26E-03) $+$	3.925E-01 (1.33E-02) $+$
	7	5.743E-01 (1.09E-02) $+$	5.587E-01 (1.56E-02) $+$	**5.564E-01** (1.13E-02) $+$	5.570E-01 (1.22E-02) $+$
WFG9	3	**5.993E-02** (1.32E-02) $+$	8.122E-02 (2.54E-02) $-$	8.912E-02 (1.83E-02) $-$	8.652E-02 (2.15E-02) $-$
	5	**3.246E-01** (1.54E-02) $+$	3.300E-01 (1.47E-02) $+$	3.325E-01 (1.63E-02) $+$	3.389E-01 (1.18E-02) $+$
	7	5.179E-01 (2.68E-02) $+$	**5.001E-01** (2.59E-02) $+$	5.252E-01 (2.03E-02) $+$	5.472E-01 (2.12E-02) $\approx$
Average rank		2.63	1.88	2.69	2.80
$+/-/\approx$		13/10/1	12/10/2	12/12/0	11/12/1

Then, we examine the performance of MOEA/D, MOEA/D-OP2, MOEA/D-FRRMAB and MA-DAC on different problems. The operator pool of FRRMAB is just the four types of DE operators. The results in Table 9 show that MOEA/D-FRRMAB is better than MOEA/D and MOEA/D-OP2, disclosing the effectiveness of adjusting the type of reproduction operators. We can also observe that the proposed MA-DAC clearly performs the best.

B.4 Analysis of the adaptive weights

In this subsection, we compare MA-DAC with MOEA/D-AWA [37], which dynamically adjusts the weights of MOEA/D based on predefined heuristic intervals. The concrete way of adjusting the weights of MOEA/D-AWA and MA-DAC are the same, as described in Appendix A.3. Table 10 shows the results, where MOEA/D-OP2-AWA refers to MOEA/D-AWA using the DE operator OP2

Table 9: IGD values obtained by MOEA/D, MOEA/D-OP2, MOEA/D-FRRMAB and MA-DAC on different problems. Each result consists of the mean and standard deviation of 30 runs. The best mean value on each problem is highlighted in **bold**. The symbols '$+$', '$-$' and '$\approx$' indicate that the result is significantly superior to, inferior to, and almost equivalent to MA-DAC, respectively, according to the Wilcoxon rank-sum test with significance level 0.05.

Problem	M	MOEA/D	MOEA/D-OP2	MOEA/D-FRRMAB	MA-DAC
DTLZ2	3	4.605E-02 (3.54E-04) $-$	4.691E-02 (3.97E-04) $-$	4.668E-02 (2.50E-04) $-$	**3.807E-02** (5.05E-04)
	5	3.006E-01 (1.55E-03) $-$	3.012E-01 (1.51E-03) $-$	3.031E-01 (1.29E-03) $-$	**2.442E-01** (1.26E-02)
	7	4.455E-01 (1.41E-02) $-$	4.551E-01 (4.43E-03) $-$	4.724E-01 (7.80E-03) $-$	**3.944E-01** (1.17E-02)
WFG4	3	5.761E-02 (5.41E-04) $-$	7.293E-02 (1.43E-03) $-$	7.097E-02 (1.63E-03) $-$	**5.200E-02** (1.19E-03)
	5	3.442E-01 (1.21E-02) $-$	2.761E-01 (6.39E-03) $-$	2.799E-01 (9.44E-03) $-$	**1.868E-01** (2.81E-03)
	7	4.529E-01 (1.79E-02) $-$	3.711E-01 (9.79E-03) $-$	3.778E-01 (1.01E-02) $-$	**3.033E-01** (3.66E-03)
WFG6	3	6.938E-02 (5.50E-03) $-$	6.714E-02 (1.59E-02) $-$	6.266E-02 (8.47E-03) $-$	**4.831E-02** (8.95E-03)
	5	3.518E-01 (2.82E-03) $-$	3.285E-01 (2.33E-02) $-$	3.272E-01 (1.61E-02) $-$	**1.942E-01** (6.90E-03)
	7	4.869E-01 (3.03E-02) $-$	4.797E-01 (3.04E-02) $-$	4.417E-01 (3.29E-02) $-$	**3.112E-01** (4.93E-03)
Train: average rank		3.11	3.00	2.89	1.00
Train: $+/-/\approx$		0/9/0	0/9/0	0/9/0	
DTLZ4	3	6.231E-02 (8.85E-02) $\approx$	6.226E-02 (4.05E-03) $-$	**5.782E-02** (3.48E-03) $-$	6.700E-02 (6.14E-02)
	5	3.133E-01 (4.45E-02) $\approx$	3.413E-01 (1.48E-02) $-$	3.373E-01 (1.70E-02) $-$	**2.995E-01** (2.10E-02)
	7	4.374E-01 (2.57E-02) $-$	4.519E-01 (1.15E-02) $-$	4.681E-01 (1.87E-02) $-$	**4.182E-01** (1.21E-02)
WFG5	3	6.327E-02 (1.10E-03) $-$	6.177E-02 (8.01E-04) $-$	6.120E-02 (7.38E-04) $-$	**4.730E-02** (7.89E-04)
	5	3.350E-01 (9.77E-03) $-$	3.052E-01 (7.19E-03) $-$	3.033E-01 (8.69E-03) $-$	**1.811E-01** (3.02E-03)
	7	4.101E-01 (2.08E-02) $-$	4.988E-01 (1.04E-02) $-$	5.045E-01 (9.70E-03) $-$	**3.206E-01** (8.04E-03)
WFG7	3	5.811E-02 (6.31E-04) $-$	6.033E-02 (8.84E-04) $-$	5.976E-02 (7.44E-04) $-$	**4.066E-02** (5.31E-04)
	5	3.572E-01 (5.47E-03) $-$	2.941E-01 (9.66E-03) $-$	3.042E-01 (1.52E-02) $-$	**1.858E-01** (2.12E-03)
	7	5.236E-01 (2.19E-02) $-$	4.739E-01 (2.51E-02) $-$	4.762E-01 (2.74E-02) $-$	**3.258E-01** (1.25E-02)
WFG8	3	8.646E-02 (3.44E-03) $-$	9.598E-02 (1.22E-03) $-$	9.536E-02 (1.14E-03) $-$	**7.901E-02** (1.19E-03)
	5	4.258E-01 (8.42E-03) $-$	3.884E-01 (1.19E-02) $-$	3.917E-01 (9.00E-03) $-$	**2.479E-01** (7.20E-03)
	7	5.816E-01 (1.30E-02) $-$	5.587E-01 (1.56E-02) $-$	5.570E-01 (1.60E-02) $-$	**4.127E-01** (5.93E-03)
WFG9	3	5.817E-02 (1.24E-03) $-$	8.122E-02 (2.54E-02) $-$	6.445E-02 (1.72E-02) $-$	**4.159E-02** (6.10E-04)
	5	3.633E-01 (1.20E-02) $-$	3.300E-01 (1.47E-02) $-$	3.312E-01 (1.70E-02) $-$	**1.832E-01** (7.10E-03)
	7	5.538E-01 (2.63E-02) $-$	5.001E-01 (2.59E-02) $-$	5.145E-01 (2.82E-02) $-$	**3.278E-01** (7.21E-03)
Test: average rank		3.13	2.87	2.80	1.20
Test: $+/-/\approx$		0/13/2	0/15/0	0/15/0	

(which has been shown to be the best among the four investigated DE operators in the last subsection) instead of the SBX operator. We can observe that MA-DAC performs the best in all problems except DTLZ4, where MOEA/D-AWA is better. Note that DTLZ4 is not used for training MA-DAC, and the worse performance than MOEA/D-AWA on this problem also implies that MA-DAC can be further improved in the future.

B.5 IGD values during the optimization process

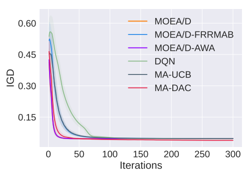
We plot the curves of IGD value of all the compared methods (i.e., MOEA/D, MOEA/D-FRRMAB, MOEA/D-AWA, DQN, MA-UCB and MA-DAC) on the problems with 3, 5 and 7 objectives of 30 runs, as shown in Figures 2, 3 and 4, respectively. We can observe that MA-DAC performs the best in general, and the superiority is more clear on the problems with 5 and 7 objectives. As the number of objectives increases, the problems become more difficult, thus requiring a powerful policy of adjusting the configuration hyperparameters. This also implies the applicability of MA-DAC in solving difficult problems.

B.6 Comparison with different DQN variants

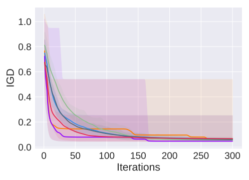
DQN has been shown the limited ability to handle large-scale action spaces [4, 5]. To improve the compared baseline, we use DQN to dynamically adjust each type of hyperparameter of MOEA/D, resulting in four DQN variants, denoted as DQN-1, DQN-2, DQN-3 and DQN-4. They represent using DQN to adjust weights, neighborhood size, types of reproduction operators, and parameters of reproduction operators, respectively. Other fixed hyperparameters' default settings are the same as those in Appendix B.1. We compare them with DQN (which dynamically adjusts all the hyperpa-

Table 10: IGD values obtained by MOEA/D, MOEA/D-AWA, MOEA/D-OP2-AWA and MA-DAC on different problems. Each result consists of the mean and standard deviation of 30 runs. The best mean value on each problem is highlighted in **bold**. The symbols '+', '−' and '≈' indicate that the result is significantly superior to, inferior to, and almost equivalent to MA-DAC, respectively, according to the Wilcoxon rank-sum test with significance level 0.05.

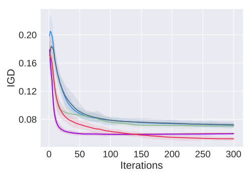
Problem	M	MOEA/D	MOEA/D-AWA	MOEA/D-OP2-AWA	MA-DAC
DTLZ2	3	4.605E-02 (3.54E-04) −	4.596E-02 (3.54E-04) −	4.670E-02 (3.30E-04) −	**3.807E-02** (5.05E-04)
	5	3.006E-01 (1.55E-03) −	2.900E-01 (2.73E-03) −	2.764E-01 (3.40E-03) −	**2.442E-01** (1.26E-02)
	7	4.455E-01 (1.41E-02) −	4.167E-01 (2.37E-02) −	4.436E-01 (8.67E-03) −	**3.944E-01** (1.17E-02)
WFG4	3	5.761E-02 (5.41E-04) −	5.748E-02 (7.11E-04) −	7.280E-02 (1.33E-03) −	**5.200E-02** (1.19E-03)
	5	3.442E-01 (1.21E-02) −	3.168E-01 (5.37E-03) −	2.648E-01 (8.15E-03) −	**1.868E-01** (2.81E-03)
	7	4.529E-01 (1.79E-02) −	4.285E-01 (1.55E-02) −	3.676E-01 (1.06E-02) −	**3.033E-01** (3.66E-03)
WFG6	3	6.938E-02 (5.50E-03) −	6.846E-02 (4.70E-03) −	6.078E-02 (1.16E-03) −	**4.831E-02** (8.95E-03)
	5	3.518E-01 (2.82E-03) −	3.190E-01 (3.93E-03) −	3.143E-01 (2.52E-02) −	**1.942E-01** (6.90E-03)
	7	4.869E-01 (3.03E-02) −	4.727E-01 (3.05E-02) −	4.770E-01 (3.24E-02) −	**3.112E-01** (4.93E-03)
Train: average rank		3.78	2.56	2.67	1.00
Train: +/−/≈		0/9/0	0/9/0	0/9/0	
DTLZ4	3	6.231E-02 (8.85E-02) ≈	**4.597E-02** (3.66E-04) ≈	6.219E-02 (3.90E-03) −	6.700E-02 (6.14E-02)
	5	3.133E-01 (4.45E-02) ≈	**2.816E-01** (3.24E-03) +	3.283E-01 (1.08E-02) −	2.995E-01 (2.10E-02)
	7	4.374E-01 (2.57E-02) −	**3.696E-01** (1.32E-02) +	4.437E-01 (9.46E-03) −	4.182E-01 (1.21E-02)
WFG5	3	6.327E-02 (1.10E-03) −	6.376E-02 (9.85E-04) −	6.168E-02 (4.61E-04) −	**4.730E-02** (7.89E-04)
	5	3.350E-01 (9.77E-03) −	3.173E-01 (5.33E-03) −	3.024E-01 (6.02E-03) −	**1.811E-01** (3.02E-03)
	7	4.101E-01 (2.08E-02) −	4.095E-01 (1.94E-02) −	4.865E-01 (1.28E-02) −	**3.206E-01** (8.04E-03)
WFG7	3	5.811E-02 (6.31E-04) −	5.837E-02 (6.25E-04) −	6.017E-02 (6.74E-04) −	**4.066E-02** (5.31E-04)
	5	3.572E-01 (5.47E-03) −	3.227E-01 (4.19E-03) −	2.885E-01 (1.25E-02) −	**1.858E-01** (2.12E-03)
	7	5.236E-01 (2.19E-02) −	5.004E-01 (3.80E-02) −	4.560E-01 (2.56E-02) −	**3.258E-01** (1.25E-02)
WFG8	3	8.646E-02 (3.44E-03) −	8.742E-02 (6.36E-04) −	9.572E-02 (8.39E-04) −	**7.901E-02** (1.19E-03)
	5	4.258E-01 (8.42E-03) −	4.216E-01 (1.18E-02) −	3.824E-01 (9.74E-03) −	**2.479E-01** (7.20E-03)
	7	5.816E-01 (1.30E-02) −	5.790E-01 (1.06E-02) −	5.632E-01 (1.27E-02) −	**4.127E-01** (5.93E-03)
WFG9	3	5.817E-02 (1.24E-03) −	5.809E-02 (1.45E-03) −	6.470E-02 (1.75E-02) −	**4.159E-02** (6.10E-04)
	5	3.633E-01 (1.20E-02) −	3.517E-01 (2.19E-02) −	3.024E-01 (1.36E-02) −	**1.832E-01** (7.10E-03)
	7	5.538E-01 (2.63E-02) −	5.108E-01 (2.65E-02) −	4.861E-01 (2.78E-02) −	**3.278E-01** (7.21E-03)
Test: average rank		3.33	2.53	2.80	1.33
Test: +/−/≈		0/13/2	2/12/1	0/15/0	



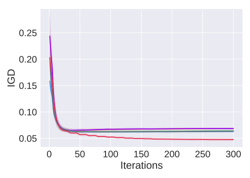
(a) DTLZ2_3



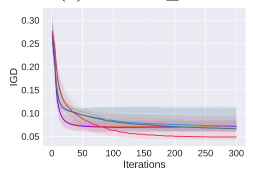
(b) DTLZ4_3



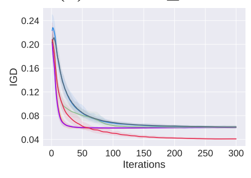
(c) WFG4_3



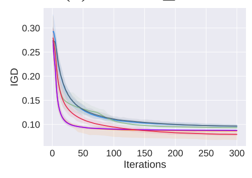
(d) WFG5_3



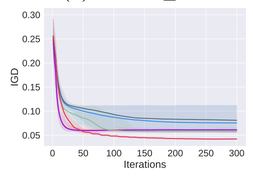
(e) WFG6_3



(f) WFG7_3

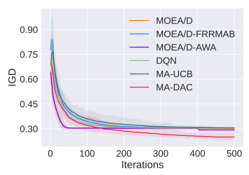


(g) WFG8_3

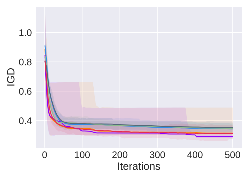


(h) WFG9_3

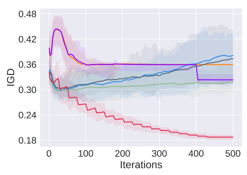
Figure 2: Curves of IGD value obtained by the compared methods on the 3-objective problems.



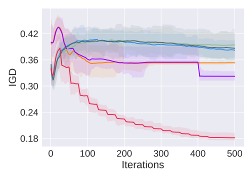
(a) DTLZ2_5



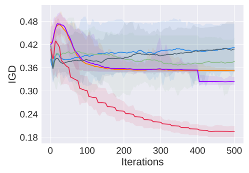
(b) DTLZ4_5



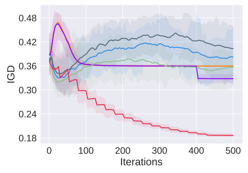
(c) WFG4_5



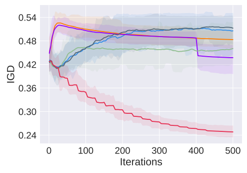
(d) WFG5_5



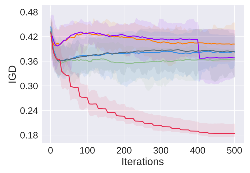
(e) WFG6_5



(f) WFG7_5

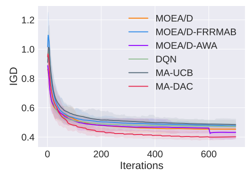


(g) WFG8_5

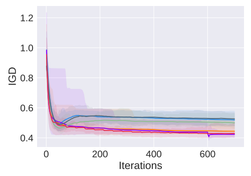


(h) WFG9_5

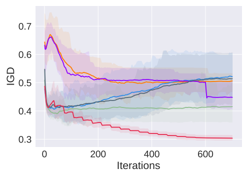
Figure 3: Curves of IGD value obtained by the compared methods on the 5-objective problems.



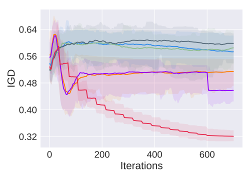
(a) DTLZ2_7



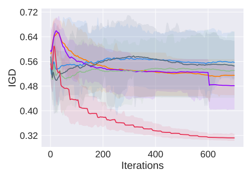
(b) DTLZ4_7



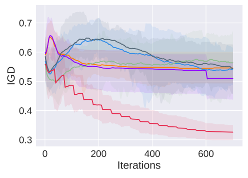
(c) WFG4_7



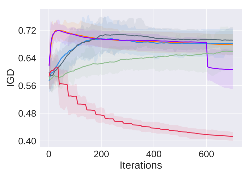
(d) WFG5_7



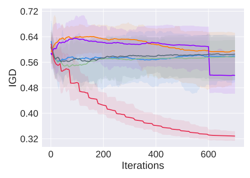
(e) WFG6_7



(f) WFG7_7



(g) WFG8_7



(h) WFG9_7

Figure 4: Curves of IGD value obtained by the compared methods on the 7-objective problems.

rameters of MOEA/D) on all the functions with 3, 5 and 7 objectives. Training functions remain the same. That is, DTLZ2, WFG4 and WFG6.

The results are shown in Table 11. As expected, all the four DQN variants outperform the DQN version that adjusts all four hyperparameters, demonstrating the ineffectiveness of using a single agent to solve complex DAC problems with large action spaces. Furthermore, it can also be observed that DQN-1 performs the best among the four DQN variants, which is consistent with the observation in Table 4, i.e., adjusting weights is generally more important.

B.7 Comparison with different MARL algorithms

To further demonstrate that the effectiveness of MA-DAC is agnostic to specific MARL algorithms, we use two more MARL algorithms as the implementations of policy networks, i.e., Independent Q Learning (IQL) [47] and QMIX [38]. IQL models each hyperparameter as an individual agent and trains each agent independently, where each agent learns an individual value function that ignores the possible effect of other agents. QMIX and VDN are value decomposition algorithms that decompose the joint value function into individual value functions. Compared to the linear value decomposition of VDN, QMIX employs a non-linear mixing network to decompose the total reward, enabling the learning of a rich joint value function.

As shown in Table 12, all the three MA-DAC policies have clear advantage over the competitive baseline DQN-1, demonstrating the effectiveness of MA-DAC. We can also see that no MARL algorithm can take a lead on all the instances, although QMIX is theoretically a better algorithm [38]. One possible reason is that the tasks' strong randomness and heterogeneity introduce new challenges.

Table 11: IGD values obtained by DQN-1, DQN-2, DQN-3 and DQN-4 on different problems. Each result consists of the mean and standard deviation of 30 runs. The best mean value of each problem is highlighted in **bold**. The symbols '$+$', '$-$' and '$\approx$' indicate that the result is significantly superior to, inferior to, and almost equivalent to DQN, respectively, according to the Wilcoxon rank-sum test with significance level 0.05.

Problem	M	DQN-1	DQN-2	DQN-3	DQN-4
DTLZ2	3	**4.100E-02** (7.64E-04) $+$	4.283E-02 (5.50E-04) $+$	4.284E-02 (3.47E-04) $+$	4.244E-02 (5.46E-04) $+$
	5	**2.408E-01** (1.03E-02) $+$	2.469E-01 (3.31E-03) $+$	2.531E-01 (3.43E-03) $+$	2.530E-01 (4.35E-03) $+$
	7	**4.064E-01** (1.14E-02) $+$	4.164E-01 (8.81E-03) $+$	4.149E-01 (8.92E-03) $+$	4.132E-01 (8.89E-03) $+$
WFG4	3	6.136E-02 (1.80E-03) $+$	6.383E-02 (1.92E-03) $+$	**5.885E-02** (1.50E-03) $+$	6.031E-02 (1.24E-03) $+$
	5	**1.887E-01** (2.15E-03) $+$	2.264E-01 (4.37E-03) $+$	2.351E-01 (5.49E-03) $+$	2.274E-01 (3.69E-03) $+$
	7	**3.018E-01** (3.14E-03) $+$	3.421E-01 (9.24E-03) $+$	3.427E-01 (9.67E-03) $+$	3.419E-01 (9.62E-03) $+$
WFG6	3	5.149E-02 (1.17E-02) $+$	**5.104E-02** (8.75E-03) $+$	6.538E-02 (2.37E-02) $+$	6.120E-02 (2.10E-02) $+$
	5	**1.991E-01** (9.10E-03) $+$	2.642E-01 (2.21E-02) $+$	2.665E-01 (1.73E-02) $+$	2.712E-01 (2.29E-02) $+$
	7	**3.204E-01** (7.11E-03) $+$	3.992E-01 (2.64E-02) $+$	3.967E-01 (2.29E-02) $+$	3.824E-01 (1.88E-02) $+$
Train: $+/-/\approx$		9/0/0	9/0/0	9/0/0	9/0/0
DTLZ4	3	**4.697E-02** (3.78E-03) $+$	5.249E-02 (1.14E-02) $+$	6.116E-02 (5.10E-02) $+$	5.469E-02 (3.65E-02) $+$
	5	**3.074E-01** (1.24E-02) $+$	3.136E-01 (1.19E-02) $+$	3.207E-01 (1.26E-02) $+$	3.243E-01 (1.75E-02) $+$
	7	4.263E-01 (1.28E-02) $+$	**4.179E-01** (1.44E-02) $+$	4.330E-01 (2.83E-02) $+$	4.211E-01 (1.21E-02) $+$
WFG5	3	**4.815E-02** (6.96E-04) $+$	5.173E-02 (7.46E-04) $+$	5.188E-02 (5.99E-04) $+$	5.175E-02 (7.38E-04) $+$
	5	**1.833E-01** (3.37E-03) $+$	2.532E-01 (5.66E-03) $+$	2.537E-01 (5.17E-03) $+$	2.560E-01 (6.80E-03) $+$
	7	**3.294E-01** (8.51E-03) $+$	4.053E-01 (1.80E-02) $+$	4.090E-01 (1.11E-02) $+$	4.088E-01 (1.34E-02) $+$
WFG7	3	**4.624E-02** (6.74E-04) $+$	4.841E-02 (1.20E-03) $+$	4.638E-02 (8.69E-04) $+$	4.690E-02 (8.85E-04) $+$
	5	**1.835E-01** (3.02E-03) $+$	2.476E-01 (7.11E-03) $+$	2.492E-01 (5.16E-03) $+$	2.445E-01 (9.30E-03) $+$
	7	**3.274E-01** (1.15E-02) $+$	3.956E-01 (1.96E-02) $+$	3.951E-01 (1.88E-02) $+$	3.843E-01 (1.81E-02) $+$
WFG8	3	8.658E-02 (1.30E-03) $+$	8.850E-02 (1.40E-03) $+$	**8.490E-02** (2.33E-03) $+$	8.555E-02 (1.59E-03) $+$
	5	**2.519E-01** (8.57E-03) $+$	3.216E-01 (1.01E-02) $+$	3.485E-01 (1.65E-02) $+$	3.328E-01 (1.29E-02) $+$
	7	**4.163E-01** (7.50E-03) $+$	5.153E-01 (1.61E-02) $+$	5.172E-01 (1.73E-02) $+$	4.970E-01 (1.12E-02) $+$
WFG9	3	7.747E-02 (2.46E-02) $-$	7.320E-02 (2.62E-02) $\approx$	**4.969E-02** (1.34E-02) $+$	6.138E-02 (2.42E-02) $+$
	5	**2.041E-01** (5.21E-03) $+$	2.542E-01 (1.03E-02) $+$	2.493E-01 (9.82E-03) $+$	2.486E-01 (1.18E-02) $+$
	7	**3.418E-01** (1.18E-02) $+$	4.088E-01 (1.71E-02) $+$	4.179E-01 (1.89E-02) $+$	4.069E-01 (1.73E-02) $+$
Test: $+/-/\approx$		14/1/0	14/0/1	15/0/0	15/0/0

We will further investigate the MARL algorithm in this regard, and meanwhile we hope that the MaMo benchmark can attract the attention of the MARL community to this type of problems.

C Experiments on DACBench

DACBench [12] is a benchmark library for DAC which collects and standardizes existing DAC benchmarks from different domains. Among these benchmarks, Sigmoid [4] is an ideal one for DAC developers to test the performance of the learned policy. Sigmoid can generate instance sets with a wide range of difficulties, e.g., by increasing the number of parameters and their configuration space dimension, or extending the heterogeneity between instances.

To formulate the instance set of Sigmoid, one needs to specify the number N_p of parameters, the size D_j of the configuration space for each parameter j, and the way to generate the distribution of the instances. For each parameter j in a given instance i, we need to choose its configuration to approximate an independent Sigmoid function

$$\mathrm{sig}(t, s_{i,j}, p_{i,j}) = (1 + e^{-s_{i,j}\cdot(t-p_{i,j})})^{-1},$$

where $s_{i,j}$ is a scaling factor, and $p_{i,j}$ is an infection point; they are the instance information for each parameter j sampled from predefined distributions. To simulate interaction effects of the individual parameters, the total reward is computed as

$$r_t = \prod_{j=1}^{N_p} \left(1 - \mathrm{abs}\left(\mathrm{sig}\left(t, s_{i,j}, p_{i,j}\right) - a_{j,t}\right)\right),$$

where $a_{j,t}$ is the configuration value for parameter j at step t.

Firstly, we conduct experiments on the $5D$-Sigmoid (i.e., there are $N_p = 5$ agents in MA-DAC) with action space size $D_j = 3$ (i.e., each agent has a 3-dimensional discrete action space). The instance

Table 12: IGD values obtained by DQN-1, VDN, IQL and QMIX on different problems. Each result consists of the mean and standard deviation of 30 runs. The best mean value of each problem is highlighted in **bold**. The symbols '+', '−' and '≈' indicate that the result is significantly superior to, inferior to, and almost equivalent to DQN-1 in Table 11, respectively, according to the Wilcoxon rank-sum test with significance level 0.05.

Problem	M	DQN-1	VDN	IQL	QMIX
DTLZ2	3	4.100E-02 (7.64E-04)	**3.807E-02** (5.05E-04) +	3.933E-02 (4.29E-04) +	3.916E-02 (7.21E-04) +
	5	2.408E-01 (1.03E-02)	2.442E-01 (1.26E-02) ≈	**2.310E-01** (9.29E-03) +	2.419E-01 (1.37E-02) ≈
	7	4.064E-01 (1.14E-02)	**3.944E-01** (1.17E-02) +	4.138E-01 (9.79E-03) −	4.162E-01 (1.59E-02) −
WFG4	3	6.136E-02 (1.80E-03)	**5.200E-02** (1.19E-03) +	5.438E-02 (8.83E-04) +	5.206E-02 (1.16E-03) +
	5	1.887E-01 (2.15E-03)	1.868E-01 (2.81E-03) +	1.879E-01 (2.78E-03) ≈	**1.859E-01** (2.25E-03) +
	7	3.018E-01 (3.14E-03)	3.033E-01 (3.66E-03) ≈	3.046E-01 (3.55E-03) −	**2.998E-01** (4.21E-03) +
WFG6	3	5.149E-02 (1.17E-02)	4.831E-02 (8.95E-03) +	5.592E-02 (1.57E-02) ≈	**4.542E-02** (3.02E-03) +
	5	1.991E-01 (9.10E-03)	**1.942E-01** (6.90E-03) +	1.981E-01 (6.76E-03) ≈	1.975E-01 (6.98E-03) ≈
	7	3.204E-01 (7.11E-03)	**3.112E-01** (4.93E-03) +	3.148E-01 (3.34E-03) +	3.128E-01 (7.39E-03) +
Train: +/−/≈			7/0/2	4/2/3	6/1/2
DTLZ4	3	**4.697E-02** (3.78E-03)	6.700E-02 (6.14E-02) ≈	6.328E-02 (4.48E-02) −	5.094E-02 (2.38E-03) −
	5	3.074E-01 (1.24E-02)	**2.995E-01** (2.10E-02) +	3.021E-01 (1.62E-02) ≈	3.013E-01 (1.80E-02) +
	7	4.263E-01 (1.28E-02)	**4.182E-01** (1.21E-02) +	4.323E-01 (1.43E-02) ≈	4.303E-01 (1.95E-02) ≈
WFG5	3	4.815E-02 (6.96E-04)	**4.730E-02** (7.89E-04) +	4.818E-02 (6.24E-04) ≈	4.736E-02 (7.49E-04) +
	5	1.833E-01 (3.37E-03)	**1.811E-01** (3.02E-03) +	1.812E-01 (2.21E-03) +	1.813E-01 (2.54E-03) +
	7	3.294E-01 (8.51E-03)	3.206E-01 (8.04E-03) +	**3.173E-01** (6.91E-03) +	3.175E-01 (7.19E-03) +
WFG7	3	4.624E-02 (6.74E-04)	**4.066E-02** (5.31E-04) +	4.313E-02 (7.79E-04) +	4.077E-02 (4.94E-04) +
	5	1.835E-01 (3.02E-03)	1.858E-01 (2.12E-03) −	1.832E-01 (2.34E-03) ≈	**1.825E-01** (3.16E-03) ≈
	7	3.274E-01 (1.15E-02)	3.258E-01 (1.25E-02) ≈	**3.219E-01** (1.09E-02) +	3.226E-01 (1.12E-02) +
WFG8	3	8.658E-02 (1.30E-03)	**7.901E-02** (1.19E-03) +	8.652E-02 (2.75E-03) ≈	7.909E-02 (1.60E-03) +
	5	2.519E-01 (8.57E-03)	**2.479E-01** (7.20E-03) +	2.544E-01 (8.10E-03) ≈	2.496E-01 (9.83E-03) ≈
	7	4.163E-01 (7.50E-03)	4.127E-01 (5.93E-03) +	4.175E-01 (7.32E-03) ≈	**4.006E-01** (9.42E-03) +
WFG9	3	7.747E-02 (2.46E-02)	**4.159E-02** (6.10E-04) +	4.423E-02 (7.08E-04) +	4.167E-02 (5.92E-04) +
	5	2.041E-01 (5.21E-03)	**1.832E-01** (7.10E-03) +	1.915E-01 (8.87E-03) +	1.921E-01 (6.43E-03) +
	7	3.418E-01 (1.18E-02)	**3.278E-01** (7.21E-03) +	3.322E-01 (8.41E-03) +	3.298E-01 (8.46E-03) +
Test: +/−/≈			12/1/2	7/1/7	11/1/3

information for each parameter is re-sampled from a predefined normal distribution at the beginning of an episode. This is a very difficult problem, and none of the learned policies in [4] can achieve satisfactory performance due to the large action space.

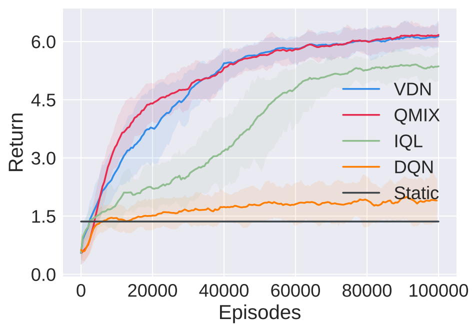
We choose the DQN in [4], and the best static policy achieved by SMAC [20] as our baselines. All the settings of experiments and baselines are consistent with [4][7]. For MA-DAC, we use three popular MARL algorithms, i.e., VDN, IQL and QMIX, as the internal implementation (see Appendix B.7 for the details of these algorithms). We implement VDN, IQL and QMIX policy networks based on the `EPyMARL`[8] [36] framework and use the default hyperparameters, except for changing the hidden layer size from 64 to 32, because of the smaller state space. The state and reward of Sigmoid for each agent in MA-DAC are same as the DQN baseline, where the only difference is that MA-DAC models each parameter as an individual agent.

As shown in Figure 5(a), all MA-DAC methods perform significantly better than DQN and static policies. The action space of the DQN agent increases exponentially with the number of parameters, making it hard to find a good policy and thus fail on this task [34, 58]. In contrast, MA-DAC can solve this task well by decomposing the action space so that each agent searches in a much smaller action space. Meanwhile, the independent learning method (i.e., IQL) is inferior to centralized training methods (i.e., VDN and QMIX). This is because the environment becomes non-stationary due to the concurrent learning of multiple learners [35].

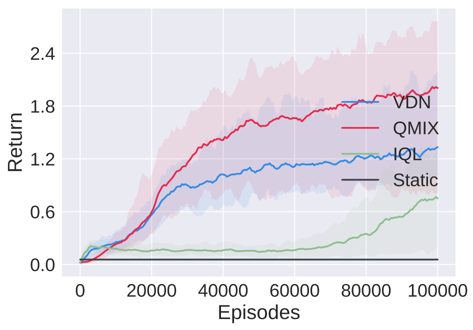
Next, to test the scalability of MA-DAC, we create another task named $10D$-Sigmoid, whose only difference from $5D$-Sigmoid is that it has 10 parameters to be configured. The DQN implementation of the DAC method cannot handle this task's ten thousand-dimensional action space due to its exponential growth in action space with the number of configured parameters. So we only take the best static policy discussed above as the baseline. As shown in Figure 5(b), all MA-DAC versions

[7]`https://github.com/automl/DAC`

[8]`https://github.com/uoe-agents/epymarl`



(a) $5D$-Sigmoid



(b) $10D$-Sigmoid

Figure 5: Curves of return value obtained by the compared methods on two Sigmoid tasks of 10 runs.

can still find higher return than static policy, demonstrating the scalability of MA-DAC. QMIX outperforms VDN due to its more accurate value decomposition from the non-linear mixing network.