Efficient Reinforcement Learning (ERL): Targeted Exploration Through Action Saturation

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**Abstract**

Reinforcement Learning (RL) generally suffers from poor sample complexity, mostly due to the need to exhaustively explore the state space to find good policies. On the other hand, we postulate that expert knowledge of the system to control often allows us to design simple rules we expect good policies to follow at all times. In this work, we hence propose a simple yet effective modification of continuous actor-critic RL frameworks to incorporate such prior knowledge in the learned policies and constrain them to regions of the state space that are deemed interesting, thereby significantly accelerating their convergence. Concretely, we saturate the actions chosen by the agent if they do not comply with our intuition and, critically, modify the gradient update step of the policy to ensure the learning process does not suffer from the saturation step. On a room temperature control simulation case study, these modifications allow agents to converge to well-performing policies up to one order of magnitude faster than classical RL agents while retaining good final performance.

**Keywords:** Reinforcement Learning, Efficient learning, Efficient exploration, Building control.

1. **Introduction**

While being successful in many applications (Coronato et al., 2020; Luong et al., 2019; Zhang et al., 2019), Reinforcement Learning (RL), and in particular its deep counterpart (DRL), usually suffer from *data inefficiency*, i.e. they typically require a significant number of interactions with the environment to converge (Duan et al., 2016; Schwarzer et al., 2021). This not only leads to significant computational costs but also limits the deployment of DRL methods on physical systems without pretraining in simulation. Indeed, in the case of building temperature control, for example, learning a policy from scratch can take years of data (Wang and Hong, 2020; Di Natale et al., 2022a).

On the other hand, we postulate that prior knowledge of physical systems often allows us to design simple rules that RL agents should follow *a priori*, such as “*Do not heat the room if it is already 26 °C*”. Interestingly, incorporating such expert knowledge in control policies is a promising step towards more efficient physics-informed RL algorithms (Du et al., 2022). In this paper, we hence propose modifications of actor-critic algorithms to encode simple rules in RL agents, introducing *artificial constraints* on the actions taken by the agents to restrict exploration to interesting regions of the state space.
While many works rely on the definition of some safe set of actions, projecting the decisions of the agents on this set at each step to constrain it, this operation is often either not differentiable (Bautista-Montesano et al., 2022) or computationally intensive (Chen et al., 2021; Gros et al., 2020). To alleviate the issue of non-differentiability without additional computational load, the main focus of this paper, one can instead let agents learn when to switch to the fallback controller (Xie et al., 2018; Hsu et al., 2022), but the satisfaction of the constraints cannot be guaranteed any more. Closer to our work, Reward Shaping (RS) might be used in various forms to penalize agents when constraints are violated, include prior knowledge to accelerate training, or let them know when a fallback controller was used even when the saturation step is not differentiable (Alshiekh et al., 2018; Hu et al., 2020; Goh et al., 2022). Such methods are however indirect, they influence the policies through the reward function that the agent will learn to optimize over time.

Contribution: In this work, we propose to saturate DRL agents’ actions when they are deemed uninteresting according to prior expert knowledge, which is encoded in simple rules. We then modify the actor update step to let agents learn from their mistakes and steer their decisions towards expected actions. Critically, the proposed modifications do not impact the complexity of the learning algorithm, are straightforward to design and implement, can be coupled with most existing actor-critic algorithms, and enforce the wanted behaviors on DRL agents by design. Their effectiveness is demonstrated in simulation on a room temperature control case study, where the proposed Efficient Agents (EAs) converge up to an order of magnitude faster than classical ones while retaining good final performance.

2. Related Work

Due to the importance of safety specifications in many applications, safe RL has gained a lot of attention in recent years, see e.g. Osinenko et al. (2022); Gu et al. (2022); García and Fernández (2015), typically relying on constrained policy optimization algorithms (Simão et al., 2021; Achiam et al., 2017). While related to our effort to accelerate the learning of RL policies, these constrained optimization methods usually impose constraints on the states of the system. On the other hand, in this work, we introduce artificial constraints on the actions taken by DRL agents to guide them and hence briefly review existing solutions to constrain the actions of or infuse prior knowledge in RL agents in this section.

Action masking: In the case of discrete action spaces, action masking can be used to block certain actions from being chosen by RL agents, artificially setting their probability to be selected to zero, see e.g. (Ye et al., 2020). This operation was shown to correspond to valid gradient updates in (Huang and Ontañón, 2020). Remarkably, Zahavy et al. (2018) trained a Neural Network (NN) to work in parallel of the policy to recognize and eliminate suboptimal actions. While the extension of action masking to deal with continuous action spaces is not trivial, Mazumder et al. (2022) similarly proposed to let agents flag uninteresting actions during the learning process to avoid revisiting them.

Safe action sets: Different from action masking, one may define a notion of safety/safe set of actions and either project the actions of the agent on this safe set at each time step or switch to a safe controller when needed (Wang et al., 2022; Mao et al., 2019; Bautista-Montesano et al., 2022; Musau et al., 2022). The main challenge with the former is that the projection operation is typically not differentiable and cannot be learned by the agent, with the notable exceptions of Chen et al. (2021); Dalal et al. (2018); Gros et al. (2020), who leveraged differentiable optimization layers.
(Chen et al., 2021), modified the policy updates to account for projections (Gros et al., 2020), or used linear constraints to derive a closed-form solution of the projection step (Dalal et al., 2018). The linear assumption was then lifted in Wang et al. (2022), but only to correct the actions of the agents online, as it cannot be used in training since no closed-form solution exists anymore.

**Data-efficient RL:** To speed up the training of RL agents, one can for example design custom exploration strategies (Lipton et al., 2018) or provide them with expert demonstrations (Nair et al., 2018), but the latter requires access to an expert policy. Alternatively, one can rely on RS to introduce prior knowledge in RL policies through more informative reward functions (Alshiekh et al., 2018; Hu et al., 2020; Goh et al., 2022). Remarkably, RS might also be used to inform RL agents about the action saturation step, typically adding a penalty to the reward function when the action chosen by the agent was overridden. This strategy, for example investigated in Alshiekh et al. (2018), is close to the modifications proposed in this work and avoids the computational overhead of differentiable optimization layers (Chen et al., 2021) or Hessian computations (Gros et al., 2020).

**Encoding simple rules:** Another idea philosophically related to the method proposed in this paper was introduced by Mao et al. (2019), who used simple rules to trigger the fallback controller and ensure safe actions are chosen. In a similar vein, Bautista-Montesano et al. (2022); Goh et al. (2022) proposed to fall back to a safe controller once bounds on certain states are reached. Contrary to the aforementioned works, we directly modify the actions taken by RL agents following given simple rules, without requiring access to a safe fallback controller or expert demonstrations. We then change the actor gradient to incorporate this knowledge directly in the learning process and not through the reward function, our method is thus agnostic to the exploration method used during training and computationally inexpensive.

### 3. Preliminaries

At each time step \( t \), given an observation \( s_t \) of the state of the environment, an RL agent chooses an action \( a_t \). The environment then transitions to \( s_{t+1} \) according to the transition probabilities \( P(\cdot | s_t, a_t) \) and sends the new state and the reward signal \( r(s_t, a_t) \) to the agent. The objective of any RL algorithm is to find a policy \( \pi(\cdot | s_t) \) that maximizes the expected discounted cumulative returns:

\[
\max_{\pi} J(\pi) = \max_{\pi} \mathbb{E}_{\pi} \left[ \sum_{t=0}^{\infty} \gamma^t r(s_t, a_t) \right],
\]

where \( \gamma \) is the discount factor trading off near- and long-term rewards, and \( \rho \) is the initial state distribution. With a slight abuse of notation on the expectation for clarity, we can define the Q-function of any state-action pair \( (s, a) \), \( Q^\pi(s, a) = \mathbb{E}_\pi \left[ \sum_{t=0}^{\infty} \gamma^t r(s_t, a_t) | s_0 = s, a_0 = a \right] \), which captures the expected returns when action \( a \) is chosen in state \( s \) and the policy \( \pi \) is followed thereafter.

In our simulations, we let agents explore the environment with the \( \epsilon \)-greedy exploration strategy, which means we apply the following action to the environment:

\[
a(s) = \text{clip}(\pi_\theta(s) + \epsilon, a^\text{low}, a^\text{up}), \quad \epsilon \sim \mathcal{N}(0, \sigma),
\]

where the noisy actions are clipped between \( a^\text{low} \) and \( a^\text{up} \), the predefined action bounds, and \( \epsilon \) is the Gaussian exploration noise with a standard deviation of \( \sigma \). All the transition tuples \( (s, a, r, s') \) observed by the agent are stored in a replay buffer.
3.1. Actor-critic algorithms

In practice, policies and Q-functions are often parametrized with NNs as $\pi_\theta$ and $Q_\phi$, respectively, leading to DRL, and numerous algorithms have been developed to solve (1) (OpenAI, 2018). In this work, we are interested in deterministic actor-critic methods, stemming from the work of Lillicrap et al. (2015), where both the actor $\pi_\theta$ (also referred to as the policy) and the critic $Q_\phi$ are optimized in parallel with gradient descent. While different flavors exist, most actor-critic algorithms compute the gradient of the critic using a variant of the Temporal Difference (TD) loss and use the critic to estimate the expected returns and derive actor gradients (Lillicrap et al., 2015):

$$\hat{\nabla}_\phi Q_\phi = \nabla_\phi \left[ \frac{1}{|B|} \sum_{(s,a,r,s') \in B} \left( Q_\phi(s,a) - \left( r(s,a) + \gamma \max_{a'} Q_\phi(s',a') \right) \right)^2 \right]$$  \hspace{1cm} (3)

$$\hat{\nabla}_\theta \pi_\theta = -\nabla_\theta \left[ \frac{1}{|B|} \sum_{s \in B} Q_\phi(s,\pi_\theta(s)) \right] ,$$  \hspace{1cm} (4)

where a batch $B$ of past transitions is sampled from the replay buffer and used to estimate expectations, (3) is the TD loss, and (4) is verified by the policy gradient theorem (Silver et al., 2014). Note that these gradients are easily computed using automatic differentiation when the actor and the critic are parametrized with NNs, see e.g. Paszke et al. (2017).

In this paper, we rely on the Twin Delayed Deep Deterministic (TD3) policy gradient algorithm, which introduces a few modifications to limit the well-known overestimation bias of Q-functions plaguing vanilla actor-critic algorithms (Fujimoto et al., 2018). Remarkably, however, these adjustments do not impact the actor gradient in (4), which allows us to seamlessly integrate the modifications detailed in Section 4 into TD3.

4. Methods

In RL applications, prior or expert knowledge often allows us to formulate simple rules that any well-performing policy should follow, such as “Immediately heat the room if the temperature is 16 °C”. This section details how to encode such simple rules in actor-critic algorithms to limit the exploration of uninteresting states, firstly by saturating actions taken by the control policy and then by modifying the gradient update of the actor accordingly to let agents learn from their mistakes.

4.1. Action saturation

In many cases, prior knowledge allows us to design a function $f$ that computes bounds on the actions we expect good policies to take in each state:

$$a^{\text{min}}(s), a^{\text{max}}(s) = f(s), \quad \text{with} \quad a^{\text{low}} \leq a^{\text{min}}(s) \leq a^{\text{max}}(s) \leq a^{\text{up}}.$$  \hspace{1cm} (5)

We can then clip the (noisy) action chosen by the policy in (2) between the provided bounds to restrict exploration to interesting parts of the state space:

$$a(s) = \text{clip}(\pi_\theta(s) + \epsilon, a^{\text{min}}(s), a^{\text{max}}(s)).$$  \hspace{1cm} (6)

Note that these bounds stemming from prior knowledge are also enforced at test time when $\epsilon = 0$. 


4.2. Modified actor gradients

One major problem when saturating the actions of the policy as suggested above is that this operation is not differentiable and the subdifferentials are zero if actions are saturated (see (8) below). Hence, we cannot backpropagate through it to let the policy learn from its mistakes. As a countermeasure, we also modify the actor gradient (4) as follows:

\[ \hat{\nabla}_\theta^{EA} \pi_\theta = -\nabla_\theta \left[ \frac{1}{|B|} \sum_{s,a \in B} Q_\phi(s, \pi_\theta(s)) - \frac{\lambda}{2} (\pi_\theta(s) - a(s))^2 \right], \tag{7} \]

where \( \lambda \) is a weighting parameter. The additional term in (7) penalizes actions chosen by the policy \( \pi_\theta(s) \) if they deviate from the constrained action \( a(s) \) that was applied to the environment, hence steering the agent’s decisions towards expected actions. Note that this modification was also successfully applied in Chen et al. (2021), in parallel to the differentiable projection on a safe set of actions, and shown to improve the convergence speed of the agents. In this work, however, we postulate that the simple gradient modification (7) can be enough to accelerate the training of DRL agents on physical systems, alleviating the computational burden of differentiable projection layers.

4.3. Implications of the modified gradients

Let \( C(s) = \{ a : a_{\text{min}}(s) \leq a \leq a_{\text{max}}(s) \} \) in any given state \( s \). Relying on the definition of the clipping operator in (6) and grouping all the parameters \( \theta \) in a vector, we can define the subdifferential \( \nabla_\theta a(s) \) of the action \( a(s) \) applied to the environment in state \( s \):

\[
a(s) = \begin{cases} 
a_{\text{min}}(s) & \text{if } \pi(s) < a_{\text{min}}(s), \\
\pi_\theta(s) + \epsilon & \text{if } \pi_\theta(s) \in C(s), \\
a_{\text{max}}(s) & \text{if } \pi(s) > a_{\text{max}}(s).
\end{cases}
\]

\[ \implies \nabla_\theta a(s) = \begin{cases} 
\nabla_\theta \pi_\theta(s) & \text{if } \pi_\theta(s) \in C(s), \\
0 & \text{else.}
\end{cases} \tag{8} \]

Introducing the Jacobian \( \nabla_\theta \pi_\theta(s) \), we can then rewrite (7) as:

\[
\hat{\nabla}_\theta^{EA} \pi_\theta = -\frac{1}{|B|} \sum_{s,a \in B} \left[ \nabla_\theta Q_\phi(s, \pi_\theta(s)) - \nabla_\theta \left[ \frac{\lambda}{2} (\pi_\theta(s) - a(s))^2 \right] \right], \tag{9}
\]

\[ = -\frac{1}{|B|} \sum_{s,a \in B} \left[ \nabla_\theta Q_\phi(s, \pi_\theta(s)) - \left[ \frac{\lambda}{2} (\pi_\theta(s) - a(s))^2 \right] \right], \tag{10} \]

We hence get the following modified actor gradient, where we omit \((s, a) \in B\) for clarity:

\[
\hat{\nabla}_\theta^{EA} \pi_\theta = \begin{cases} 
-\frac{1}{|B|} \sum_B [\nabla_\theta Q_\phi(s, \pi_\theta(s))] & \text{if } \pi_\theta(s) \in C(s), \\
-\frac{1}{|B|} \sum_B [\nabla_\theta Q_\phi(s, \pi_\theta(s)) - \lambda \nabla_\theta \pi_\theta(s)^T (\pi_\theta(s) - a(s))] & \text{else.}
\end{cases} \tag{11}
\]

Remarkably, the additional penalty term allows us to solve the issue of the subdifferentials of the clipping operator being zero when actions are saturated, modifying the gradients exactly when the constraints are not met. Indeed, as long as the action chosen by the agent respects the constraints provided by \( f \), the classical gradient (4) is used. On the other hand, as soon as the constraints are not met, the gradient is modified in the direction \([\pi_\theta(s) - a(s)]\) to accelerate the convergence of \( \pi_\theta(s) \) to \( C \), despite the subdifferential of the clipped action being zero. This allows agents to learn from their mistakes and rapidly converge to interesting policies.
5. Room temperature control case study

To assess the effectiveness of the proposed method, we apply it to a building control case study, where the objective is to minimize the energy consumption of a room while maintaining the comfort of the occupants, represented by predefined temperature bounds that should not be exceeded.

5.1. Reinforcement Learning framework

The continuous action space of the agents corresponds to how much heating power, respectively cooling power, should be applied at each time step, normalized between $a^{\text{low}} = -1$ and $a^{\text{up}} = 1$. During the heating season, $a^{\text{low}}$ corresponds to the heating being turned off, and $a^{\text{up}}$ to full heating, and the contrary in the cooling case. Physically Consistent Neural Networks (PCNNs) (Di Natale et al., 2022b) are used to simulate the behavior of one bedroom in the NEST building (Empa, 2022).

The reward function is defined as the negative weighted sum of energy consumption $E_t$ and comfort violations, i.e. how far from the designed bounds the temperature inside the room is. Mathematically, we thus have:

$$r(s_t, a_t) = -\max \{L_t - T_t, 0\} - \max \{T_t - U_t, 0\} - \alpha E_t,$$

where $L_t$ and $U_t$ represent the lower and upper comfort bounds on the temperature $T_t$ at time $t$, respectively, $\alpha$ is a weighting factor, and $E_{\text{heat}}^{\text{max}}$ and $E_{\text{cool}}^{\text{max}}$ stand for the maximal heating and cooling power. More details on the experimental setup can be found in Di Natale et al. (2022a).

5.2. Design of the saturation rules

In the context of room temperature control, we intuitively know that an optimal policy should slowly stop heating when the temperature reaches the upper comfort bound and slowly start heating as soon as the lower bound is not met (and the contrary for cooling), typically to avoid criticism from the occupants. To encode these simple rules, we design $f$ as follows:

$$a^{\text{min}}(s_t) = \text{clip} \left( \frac{(L_t - m) - T_t}{n - m}, 0, 1 \right)^2 \cdot 2 - 1$$

$$a^{\text{max}}(s_t) = 1 - 2 \cdot \text{clip} \left( \frac{T_t - (U_t + m)}{n - m}, 0, 1 \right)^2,$$

with $n \geq m \geq 0$ representing design parameters to leave more or less freedom to the agents. In words, we start constraining the action of the agents as soon as the temperature deviates from the bounds for more than $m$ degrees and then quadratically increase the constraint until $n$ degrees have been reached, where the agent is forced to use the maximum or minimum power. As can be seen, $a^{\text{min}}(s_t) > -1$ only when the temperature is below the lower comfort bound, and $a^{\text{max}}(s_t) < 1$ only when it exceeds the upper one.

6. Results

We trained several Efficient Agents with different parameters $m$ and $n$ (EA $m / n$) to minimize the energy consumption while maintaining the comfort of the occupants. For comparison purposes, we
also trained agents with the classical actor gradient (4), introducing the additional squared penalty $\frac{1}{2} (\pi_\theta(s) - a(s))^2$ in the reward function instead as another computationally inexpensive means to incorporate prior knowledge in DRL agents (RS $m / n$).

All the agents were trained on up to three-day-long episodes randomly sampled from three years of data. They were evaluated after each 96 steps of 15 min, i.e. one day’s worth of data, hereafter also referred to as an epoch, on a testing set of 50 unseen sequences of three days to monitor their progress during the first 500 epochs. The code used to generate these results will be made available on https://gitlab.nccr-automation.ch/loris.dinatale/efficient-drl.

6.1. Visualization of the impact of the proposed modifications

To intuitively understand the effect of action saturation, we first visualize its impact on some EAs in Figure 1, where the behavior of all agents is plotted before training on the left, and after on the right, for the same three days in March, i.e. during the heating season. Focusing on the left plot, we see the untrained classical DRL agent in black letting the temperature diverge to an uncomfortably high range (out of the bounds of the plot) as it starts exploring the state space using roughly constant heating power. On the other hand, all the EAs are forced to stop heating once they are $n$ degrees out of bounds. Consequently, even before training, such agents will not overheat the room and keep it at acceptable temperatures for the occupants, which corresponds to what we expect from good control policies. This can however lead to control input oscillations due to the impact of external disturbances, mainly the solar gains around noon, which sometimes trigger the overriding mechanism and forces them to suddenly stop heating.

On the right plot, after training, one can observe that all EAs generally take comparable decisions leading to similar temperature patterns, still with some control oscillations stemming from the
overriding mechanism. On the other hand, the classical DRL agent presents a slightly different behavior, with smoother decision patterns. Interestingly, this agent is the only one heating in the early afternoon, while the EAs wait until the end of the afternoon to heat the room with high power and meet the comfort bound tightening at 8pm. As presented in Table 1, this allows the classical agent to use less energy than EAs over these three days, but it might incur additional comfort violations. As shown in Appendix A, these findings generalize to the entire data set: classical DRL agents usually use less energy at the cost of additional comfort violations compared to EAs in the early phase of learning, before converging to near-optimal solutions after longer training times (Di Natale et al., 2022a). In fact, choosing a smaller $n$, i.e. incorporating more prior knowledge in the EAs, allows them to satisfy the comfort bounds faster without significant additional energy consumption.

### 6.2. Data efficiency

A comparison of the convergence speed of various agents over the first 300 epochs is plotted in Figure 2, where the vertical lines and annotations illustrate the number of days required to attain performance on par with rule-based on-off industrial baselines from Di Natale et al. (2022a). In general, we observe that all the EAs attain returns on par with the baselines significantly earlier than classical DRL agents, in as little as 29 days instead of roughly 200, an improvement of almost an order of magnitude. In particular, the smaller $n$ is chosen (from left to right in Figure 2), the faster the convergence of the EAs in green and blue. Intuitively, this makes sense, as tighter constraints introduce more prior knowledge to the EAs, thereby allowing them to find interesting solutions faster, without losing time exploring the state space. On the other hand, the influence of $m$ is less marked, with $m \neq 0$ (blue) and $m = 0$ (green) leading to very similar convergence patterns (bottom line of plots).

Remarkably, RS does not seem to drastically speed the training up in this case study (red). While RS 0 / 0.25 does converge twice as fast as the classical DRL agents, we can also observe that RS 0 / 0.1 did not converge at all, hinting at the fragility of RS in general. On the other hand, it seems to lead to more consistent performance than classical DRL agents and EAs after a few hundred epochs, which is confirmed by their good final performance, as detailed in Appendix A.

Overall, these results support our claim that, as long as the rules in $f$ are well-defined and correspond to expected behaviors, the proposed modifications can indeed greatly accelerate the convergence of DRL agents. Critically, however, this does not significantly impact the quality of the final solution, as shown in Appendix A. Interestingly, incorporating more specific expert knowledge in EAs, i.e. using tighter $m/n$ parameters, further accelerates the convergence of EAs. This again corresponds to our intuition: tighter and better-defined rules help the agents more. Remarkably, the modifications proposed in Section 4 provide the desired speedup for a wide variety of parameters $m/n$, contrary to RS, hinting at the robustness of the proposed scheme.
7. Conclusion

Starting from the postulate that prior expert knowledge often gives us an intuition of how good control policies should behave, we presented a scheme to encode it through simple rules in DRL agents to accelerate the learning procedure and decrease the associated computational load. These rules take the form of bounds on the agent’s actions at each time step, which can directly be enforced during offline training and online operations without overhead. Additionally, to ensure agents learn from their mistakes, we modify the gradients used to update the parameters of the actor to steer control policies towards expected behaviors, limiting the exploration of uninteresting states.

On a room temperature control case study, this scheme allowed us to accelerate the convergence speed of DRL agents by up to an order of magnitude. Furthermore, modifying actor gradients proved to be more effective and more robust than the widespread reward shaping method. Remarkably, this was done without suffering from a significant drop in the final performance of the control policies, illustrating how prior knowledge can help reduce the computational costs as long as the rules defined by the user match the behavior of optimal policies. This represents an interesting first step towards DRL agents that can be deployed and learned from scratch on physical systems, potentially bypassing the need for complex simulators. In future work, it would hence be interesting to investigate annealing strategies on $\lambda$ to slowly alleviate the additional penalty in the actor gradient and let agents learn more expressive policies once the initial exploration phase has been carried on.
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Appendices

Appendix A. Additional results

The best reward obtained by all the trained agents over the first 500 epochs can be found in Table 2, and the corresponding trade-off between energy consumption and comfort violations is plotted in Figure 3. These snapshot results after 500 epochs also illustrate how tighter constraints, i.e. higher levels of prior knowledge, allow EAs and RSs to converge to better solutions in this limited training regime.

| Agent          | Reward | Agent          | Reward | Agent          | Reward |
|----------------|--------|----------------|--------|----------------|--------|
| Classical DRL 1| -2.64  | Classical DRL 2| -2.75  | EA 0.5-1       | -2.83  |
| RS 0-1         | -2.58  | EA 0-1         | -2.85  | EA 0.25-0.5    | -2.74  |
| RS 0-0.5       | -2.44  | EA 0-0.5       | -2.58  | EA 0.2-0.25    | -2.62  |
| RS 0-0.25      | -2.37  | EA 0-0.25      | -2.51  | EA 0.2-0.25    | -2.62  |
| RS 0-0.1       | -3.69  | EA 0-0.1       | -2.46  | EA 0.075-0.1   | -2.46  |

Table 2: Best reward obtained by each agent on the test set over the first 500 epochs.

Figure 3: Best trade-off between energy consumption and comfort violations found by different agents on the testing set over the first 500 epochs. For comparison purposes, the performance of two industrial baselines, of an agent trained for 125'000 epochs (Best Agent), and the optimal performance achievable (all computed as in Di Natale et al. (2022a)), are also reported in grey.
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EFFICIENT REINFORCEMENT LEARNING (ERL): TARGETED EXPLORATION THROUGH ACTION SATURATION

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