Combining off-Policy and on-Policy Reinforcement Learning for Dynamic Control of Nonlinear Systems

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Abstract: This paper introduces QARSA, a novel reinforcement learning algorithm that combines the strengths of off-policy and on-policy methods, specifically Q-learning and SARSA, for the dynamic control of nonlinear systems. Designed to leverage the sample efficiency of off-policy learning while preserving the stability and lower variance of on-policy approaches, QARSA aims to offer a balanced and robust learning framework. The algorithm is evaluated on the CartPole-v1 simulation environment using the OpenAI Gym framework, with performance compared against standalone Q-learning and SARSA implementations. The comparison is based on three critical metrics: average reward, stability, and sample efficiency. Experimental results demonstrate that QARSA outperforms both Q-learning and SARSA, achieving higher average rewards, stability, sample efficiency, and improved consistency in learned policies. These results demonstrate QARSA's effectiveness in environments were maximizing long-term performance while maintaining learning stability is crucial. The study provides valuable insights for the design of hybrid reinforcement learning algorithms for continuous control tasks.

1 INTRODUCTION

Reinforcement Learning (RL) has become a prominent approach in developing intelligent agents capable of learning optimal behaviors through interactions with their environment. Central to this paradigm is the reward signal, which the agents aim to maximize over time. The flexibility and effectiveness of RL have made it widely applicable across diverse domains such as robotics and game playing, cementing its importance in artificial intelligence research (AlMahamid & Grolinger, 2022).

Among various RL methodologies, temporal difference (TD) learning stands out for its capacity to learn from direct interactions without explicit environmental models.

This paper introduces a novel reinforcement learning algorithm, QARSA, combining off-policy and on-policy learning approaches, specifically Q-learning and SARSA. Off-policy methods like Q-learning emphasize past experiences, enhancing the accumulation of rewards, sample efficiency, and facilitating rapid learning. Conversely, on-policy methods such as SARSA directly utilize the current policy in their updates, resulting in greater stability and lower variance. By merging these complementary features, QARSA, the novel algorithm proposed in this work, aims to achieve improved rewards and sample efficiency alongside increased stability.This is particularly suitable for dynamic control scenarios involving nonlinear systems.

To evaluate the effectiveness of QARSA, this work applies the algorithm to the classical cart-pole problem, a well-established benchmark for assessing RL performance in control tasks. The cart-pole environment requires the agent to balance a pole upright on a moving cart by applying directional forces, exemplifying the critical balance between

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exploration and exploitation required for successful control (Surriani et al., 2021).

Therefore, this paper aims to analyze and compare the performance of QARSA, Q-learning, and SARSA on the cart-pole problem. This comparison will provide valuable insights into the relative strengths and limitations of each algorithm. Additionally, this paper analyzes the learning curves, final outcomes, hyperparameter sensitivity, and the impact of various function approximation techniques. Through this comprehensive analysis, the strengths and weaknesses of the new QARSA algorithm are highlighted, contributing valuable insights into its practical applicability and scalability in reinforcement learning for control tasks.

2 BACKGROUND WORK

Two of the most fundamental model-free methods in RL are Q-Learning and SARSA. Both fall under the category of Temporal-Difference (TD**)** learning, and update a value function based on the agent's experience without requiring a model of the environment.

Sutton & Barto, (2018) highlighted that SARSA's conservative update mechanism can yield superior performance in environments where cautious exploration strategies are beneficial. Double Q-learning (Van Hasselt et al., 2016) and Weighted Q-learning (Cini et al., 2020) address the overestimation bias inherent in traditional Q-learning, leading to enhanced stability and improved outcomes, particularly in environments characterized by high complexity and variability in action-value functions. Several comparative analyses have investigated how RL algorithm performance can be influenced by exploration methods (e.g., ε-greedy, softmax), reward shaping, and discretization strategies such as those by Tokic (2010). These elements are particularly critical in continuous-state environments like the cart-pole task, which require discretization for tabular RL methods.

Nagendra et al. (2017) and Zhong (2024) conducted comparisons of various RL algorithms, emphasizing sample efficiency and stability. However, a thorough comparative analysis explicitly evaluating Q-learning and SARSA based on cumulative rewards per episode in this environment remains under-explored. Mothanna & Hewahi (2022) demonstrated the applicability of Q-learning and SARSA in solving the cart-pole problem, proposing future work to extend the analysis to additional RL algorithms.

Despite these developments, limited direct comparative work specifically addresses the learning efficiency, stability, and ultimate performance of Q-learning and SARSA in the cart-pole environment. Most existing comparative studies have either examined more complex tasks or employed different evaluation metrics. Those works that focus on the cart-pole problem utilize the OpenAI Gym simulation framework and include metrics such as average reward, stability, sample efficiency, and overall effectiveness (Brockman et al., 2016).

In (Hazza et al.,2025) the performances of three reinforcement learning algorithms were collectively compared under a sensitivity analysis in which all hyperparameter values were systematically varied to observe their impact on the learning process. While Q-learning exhibited marginally higher average and cumulative rewards, the differences among Q-learning, SARSA, and Double Q-learning were not substantial across the tested range, indicating that no single method decisively outperforms the others.

Q-Learning and SARSA represent two fundamentally different approaches to value-based learning (Kommey et al., 2024) . Q-Learning is an off-policy algorithm that learns the value of the optimal policy independently of the agent's actions. While effective in many deterministic environments, its reliance on the maximum Q-value in the update step can lead to overestimation bias and instability in noisy or stochastic environments. In contrast, SARSA is an on-policy method that learns the value of the policy the agent is actually following. It tends to be more stable and risk-averse, especially in unpredictable environments, but often converges more slowly and may be overly conservative (Wang et al., 2013).

With this in mind, this work proposes a novel hybrid approach, designed to merge the strengths of on-policy and off-policy reinforcement learning methods, and tested by simulation on the cart-pole problem, as detailed in the rest of the paper.

2.1 Q-Learning Algorithm

Q-learning is one of the most widely used RL algorithms, renowned for its simplicity and effectiveness, introduced by Watkins in 1989 (Watkins & Dayan, 1992). It is an off-policy algorithm that estimates the optimal action-value function $Q(s, a)$ by learning from the maximum future reward, regardless of the agent's current policy. Its update rule is defined by Equation (1):

$$Q(s,a) \leftarrow Q(s,a) + \alpha\,[r + \gamma \max_{a'} Q(s',a') - Q(s,a)] \quad (1)$$

Here, $Q(s, a)$ denotes the Q-value of taking action a in state s, α is the learning rate, γ is the discount factor, r is the immediate reward, and s' is the next state after action a, and a' is the action taken in the next state s'. The use of the maximum Q-value over next actions a' makes Q-Learning optimistic and efficient in deterministic settings, but it can suffer from overestimation in noisy environments.

2.2 SARSA Algorithm

SARSA (State-Action-Reward-State-Action) refers to an on-policy method that updates the value function based on the actual actions taken by the agent under its current policy (Sutton & Barto, 2018).

The SARSA update rule is given by Equation (2):

$$Q(s,a) \leftarrow Q(s,a) + \alpha\,[r + \gamma\, Q(s',a') - Q(s,a)] \quad (2)$$

In this case, a' is the next action actually chosen by the policy, not necessarily the one with the maximum value. This makes SARSA more conservative and safer in stochastic environments, as it learns the action-values according to the policy being followed.

Previous studies, such as those by Singh and Sutton (1996), have compared these two algorithms under various conditions. SARSA tends to perform better in environments with high variability or where risk-averse behavior is preferred, while Q-Learning often converges faster in deterministic tasks.

2.3 QARSA: A Hybrid Reinforcement Learning Algorithm

Recognizing the complementary strengths and weaknesses of Q-Learning and SARSA algorithms, we propose QARSA (a hybrid of the two). This algorithm combines the update rules of both Q-Learning and SARSA via a tunable blending parameter $\lambda \in [0,1]$.

By adjusting λ, QARSA can strike a balance between the aggressive, policy-independent updates of Q-Learning and the cautious, policy-aware updates of SARSA. This makes it particularly suited for environments that exhibit both deterministic and stochastic behaviors. We evaluate QARSA against its parent algorithms to assess performance differences using simulation experiments in a the cart-pole control environment.

2.3.1 QARSA Update Rule

The QARSA update rule is given by Equation (3):

$$Q(s,a) \leftarrow Q(s,a) + \alpha\big[r + \gamma\big(\lambda \max_{a'} Q(s',a') + (1-\lambda)Q(s',a')\big) - Q(s,a)\big] \quad (3)$$

where s is the current state, a is the current action, r is the reward, s' is the next state, a' is the action taken in state s' (based on policy), α is the learning rate, γ is the discount factor, and λ is the blending factor, controlling the mix between Q-Learning and SARSA.

This update rule allows for a weighted combination between on-policy and off-policy learning.

By adjusting λ, the agent can adopt a learning style that is best suited to the environment's characteristics.

2.3.2 Behaviour and Interpretation

When $\lambda \rightarrow 1$: QARSA is equivalent to Q-Learning, using the maximum expected return for future actions. This can speed up learning but risks overestimating the value function in stochastic environments.

When $\lambda \rightarrow 0$: QARSA reduces to SARSA, basing the value update on the actual action taken. This often results in safer but slower learning.

Intermediate λ: Provides a **balance**; the agent is neither too optimistic nor too cautious, which can lead to improved stability and better generalization.

3 METHODOLOGY

3.1 Environment Setup

The cart-pole problem is a well-known benchmark in the use of reinforcement learning for control systems. It is favoured for its straightforward design and fast training time. However, its simplicity also limits its applicability, meaning that insights gained from this task may not extend well to more complex scenarios, particularly those that involve continuous action spaces or high-dimensional visual inputs. The RL model for this setup is shown in Figure 1. In this task, the agent's goal is to keep the pole balanced in the inverted position by applying forces to move the cart either left or right. The following considerations are to be noted:

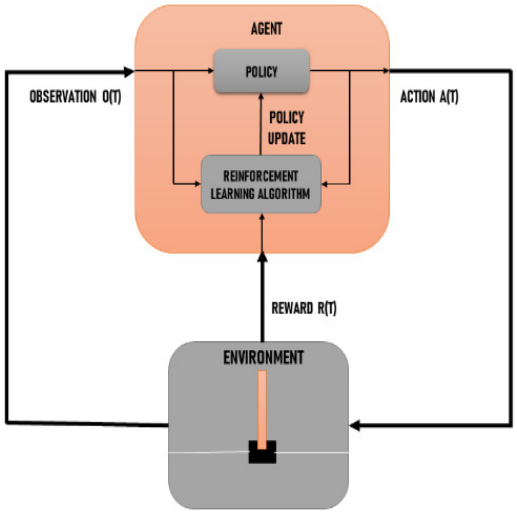

Figure 1: The Reinforcement Learning Model for The Cart Pole Problem.

- **State Space:** This consists of the system's state variables that describe the system's dynamics.

The state space consists of four continuous parameters: The cart position (x), which can vary within the range of -2.4 to +2.4 meters, the pole angle (θ) that in this set-up will range from -0.2095 to +0.2095 radians (equivalent to -12° to +12 °), the cart velocity (ẋ), and the pole angular velocity ($(\theta)^{\cdot}$). The last two are unbounded and can take any value (Mishra & Arora, 2023).

- **Action Space:** The action space is discrete and consists of two possible moves:
  0: Apply force to push the cart to the left, and
  1: Apply force to push the cart to the right.

The resulting state depends on the action taken. For example, as illustrated in Figure 2, if the system starts with the pole in an upright position and the cart is pushed to the left, the pole typically leans to the right, leading to a new state, and vice versa.

- **Reward Structure:** The agent earns a reward of +1 for every time step that the pole angle remains within the ± 12° angle range.

If the pole tilts beyond ±12 degrees or when the cart position exceeds the horizontal boundary of ±2.4m from the centre, that specific episode of the simulation is stopped. An episode is also stopped if the pendulum angle and position remain within the prescribed ranges for up to 500 time steps, corresponding to 10 seconds of simulated time, with each step representing 20 milliseconds, this being considered as constituting successful balancing control for a significant amount of time (Li et al., 2024).

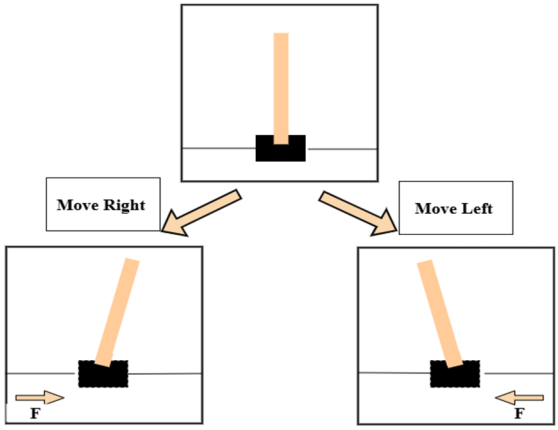

Figure 2: Typical Actions Performed by The Cart Pole Problem.

3.2 Algorithm Implementation

As this study aims to implement and compare the Q-learning, SARSA, and QARSA algorithms, they were developed using the same core parameters to ensure a fair and consistent evaluation. Q-learning is implemented using a tabular approach, where the action-value function $Q(s, a)$ is stored in a table and updated using the Bellman Equation 1. Similarly, SARSA is applied as a tabular method, but its Q-value updates incorporate the action taken in the next state, following the SARSA update rule in Equation 2. QARSA combines elements of both Q-learning and SARSA, as described in Section 2.3.

Table 1 presents the hyperparameter values identified through experimental trials as having the most significant influence on the algorithms' performance (Jumaah et al., 2025). These parameter values were chosen based on established practices in the literature and were fine-tuned to enhance the overall performance of all three algorithms. The second column of Table 1 displays the optimized values found by experimentation to yield the best results.

Table 1: Hyperparameter values of Q-Learning, SARSA, and QARSA algorithms for the Cart Pole Problem.

Hyperparameter	Value
Learning Rate α	0.09
Discount Factor γ	0.07
Blending factor λ	0.5
Exploration Strategy ϵ	0.995
Number of Episodes	5000
Max Steps per Episode	500

3.3 Experimental Procedure

The experimental process was structured as follows: Each algorithm began by initializing the Q-table(s) to zero for all state-action pairs. Training commenced by resetting the CartPole-V1 environment to initialize the starting state for each episode. Actions were selected using the epsilon-greedy policy, primarily choosing the action with the highest estimated reward. The selected action was executed, after which the environment's reward and next state were observed. Subsequently, the Q-value(s) were updated according to the algorithm-specific update rule. If an episode concluded due to the pole falling or the cart moving out of bounds, the total accumulated reward for that episode was recorded.

3.4 Performance Metrics

The following metrics were employed to assess the algorithm performance (Escobar et al., 2020):

- **Average Reward:** Calculated as the mean total reward received per episode throughout the training period, serving as a primary indicator of algorithm efficacy.
- **Stability:** This metric assesses the consistency of algorithm performance once convergence is achieved. Stability was quantified by calculating the standard deviation of rewards over the final 100 episodes, with lower values indicating higher stability and consistent behavior.
- **Sample Efficiency:** This evaluates how effectively an algorithm improves its performance given limited experiences. Specifically, sample efficiency was measured by the cumulative reward obtained over the first 1000 episodes, reflecting how rapidly each algorithm learns an effective policy.

3.5 Computational Issues

All algorithms and simulations were implemented using Python 3.10 with the following essential libraries: the OpenAI Gym: CartPole-v1 environment, NumPy for numerical computation, and Matplotlib for visualization and plotting of learning curves. Experiments were executed on a standard computer equipped with a 12th Gen Intel(R) Core (TM) i9-12900K 3.20 GHz processor, 32.0 GB RAM, and NVIDIA® GeForce RTX™ 4090 GPU to run the simulations in a reasonable time.

Evaluation becomes computationally expensive due to the rapid growth of the state and action spaces as discretization increases. For instance, discretizing the state variables cart position, cart velocity, pole angle, and pole angular velocity into fixed intervals significantly expands the size of the state-action space, leading to increased computational overhead and complexity in learning and decision-making possible state-action (Tallec et al., 2019). As a result, the Q-table grows exponentially with finer discretization, significantly increasing memory requirements and the computational overhead for value updates during training. Moreover, each simulation involves frequent table lookups, policy evaluations, and Q-value updates, all of which scale with the size of the discretized space.

This necessitates high-performance computational resources, especially when running repeated trials across multiple algorithms to study the statistical significance of the results in comparative analyses (Gogineni et al., 2024).

4 RESULTS AND DISCUSSION

The performance of the Q-learning, SARSA, and QARSA reinforcement learning algorithms was assessed using the previously described metrics across 5,000 episodes. The first results are illustrated in the learning curves shown in Figure 3. All three algorithms demonstrate rapid progress during the first 1,000 episodes, suggesting fast initial learning, but also display significant variability in their performance.

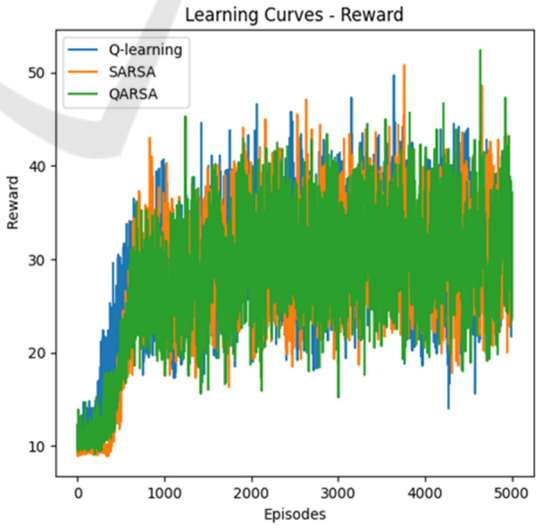

Figure 3: Reward Performance of Q-Learning, SARSA, and QARSA Algorithms for The Cart Pole Problem.

This pattern may reflect the agent's exploration of various strategies or challenges in consistently

maximizing rewards, potentially due to a non-stationary or highly stochastic environment.

The frequent intersections of the learning curves further support the notion that the algorithms perform comparably overall, with no single method clearly outperforming the others throughout all episodes. This observation is consistent with the average reward results that highlight QARSA's slight advantage in overall performance, as illustrated in Figure 4.

QARSA attained the highest average reward (28.74) with a total of 143712.4 rewards, followed closely by Q-learning average reward (28.45) with a total of 142264.9 rewards, and then SARSA average reward (28.06) with a total of 140319.2 rewards.

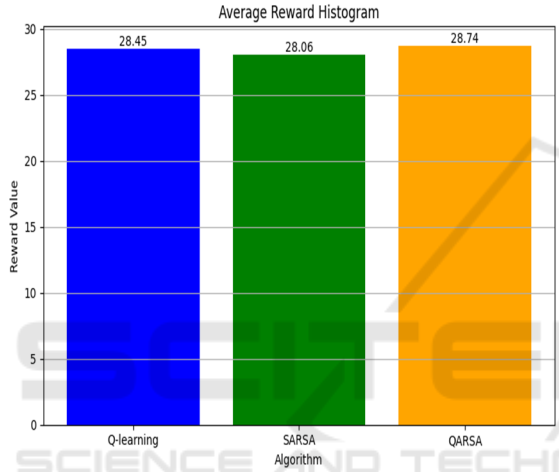

Figure 4: The Average Reward of Q-Learning, SARSA, and QARSA Algorithms for The Cart Pole Problem.

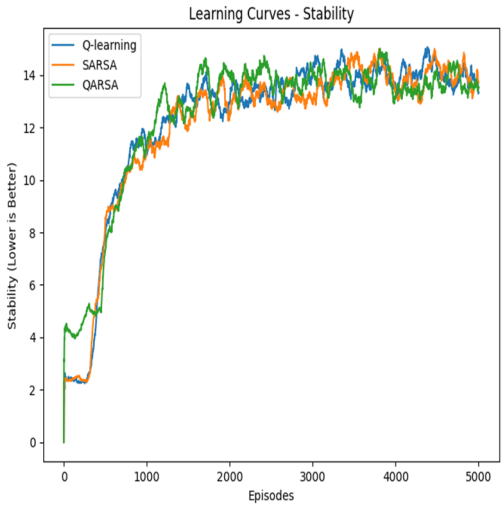

Figure 5: Stability Performance of Q-Learning, SARSA, and QARSA Algorithms for The Cart Pole Problem.

The slight differences in average rewards suggest that all three algorithms performed similarly regarding overall effectiveness. However, QARSA's slightly higher average reward indicates it may have a marginal advantage in maximizing long-term returns.

The stability metrics for all three algorithms were also comparable, with SARSA showing slightly better stability (14.18) compared to Q-learning (14.37) and QARSA showing the best stability (13.89), as shown in Figures 5 and 6.

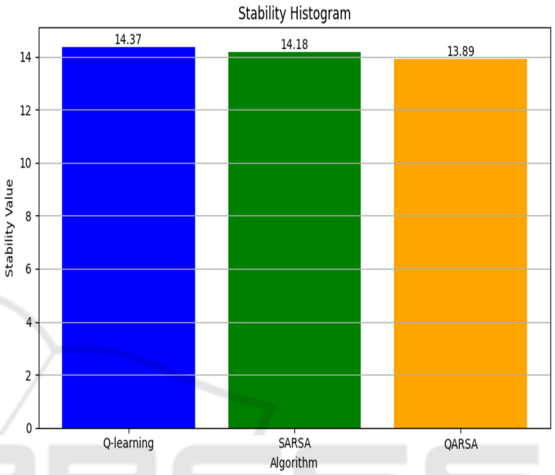

Figure 6: Stability of Q-Learning, SARSA, and QARSA Algorithms for The Cart Pole Problem.

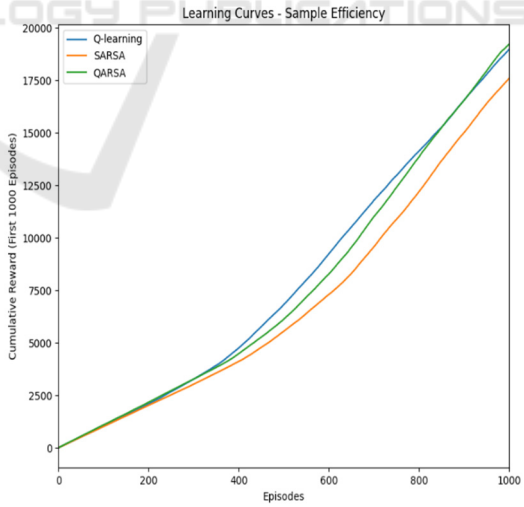

Figure 7: Sample Efficiency Performance of Q-Learning, SARSA, and QARSA Algorithms for The Cart Pole Problem.

As shown in Figures 7 and 8, QARSA demonstrated the best sample efficiency (19212), followed by Q-learning (18964.4) and SARSA (17585.2). QARSA

may learn more effectively from fewer experiences, potentially making it more suitable for environments where data collection is costly or limited.

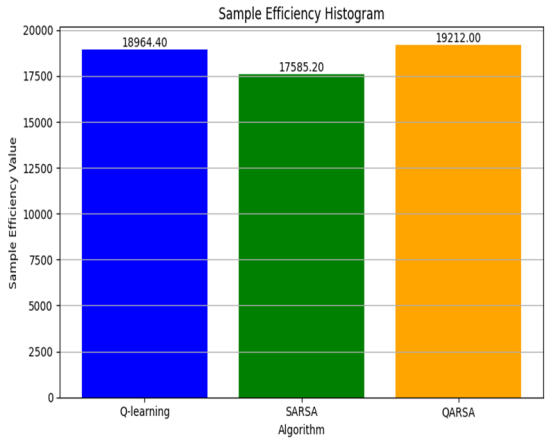

Figure 8: The Sample Efficiency of Q-Learning, SARSA, and QARSA Algorithms for The Cart Pole Problem.

Table 2 summarizes the final metrics obtained in the three algorithms for the Cart Pole Problem, where the best results are highlighted in grey.

Table 2: The Performance Comparison of Q-Learning, SARSA, and QARSA for The Cart Pole Problem.

Metrics	Q-Learning	SARSA	QARSA
Total Rewards	142264.9	140319.2	143712.4
Average Reward	28.45	28.06	28.74
Stability	14.37	14.18	13.89
Sample Efficiency	18964.4	17585.2	19212

4 CONCLUSIONS AND FUTURE WORK

This paper proposed QARSA, a novel reinforcement learning algorithm that integrates off-policy and on-policy learning principles by combining Q-learning and SARSA. QARSA was evaluated in the CartPole-v1 environment and compared against its constituent algorithms. Simulation results demonstrated that for the cart-pole problem, QARSA marginally outperformed both Q-learning and SARSA across all key performance metrics, achieving higher average rewards, greater stability, and higher sample efficiency. These results suggest investigating further the performance of the proposed QARSA hybrid reinforcement learning method for dynamic control settings. Future work will thus focus on testing QARSA in other complex environments, not only the cart-pole problem, to investigate its scalability to continuous state and action spaces, and explore methods for determining the optimal value of the blending factor between Q-learning and SARSA, which is possibly dependent on the characteristics of the system being controlled and the desired control tasks. Finally, we will rigorously investigate the comparative performance between the three algorithms through Monte Carlo analysis and statistical significance tests. Each algorithm has its strengths, and literature shows that the choice of optimal hyperparameters depends on the scenario defining the problem and the specific requirements of the task at hand (Manglik & Tripathi, 2018).

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REFERENCES

AlMahamid, F., & Grolinger, K. (2021). *Reinforcement Learning Algorithms: An Overview and Classification*. 2021 IEEE Canadian Conference on Electrical and Computer Engineering (CCECE), 2021, pp. 1-7

Brockman, G., Cheung, V., Pettersson, L., Schneider, J., Schulman, J., Tang, J., & Zaremba, W. (2016). *OpenAI Gym*. arXiv.org. https://arxiv.org/abs/1606.01540.

Cini, A., D'Eramo, C., Peters, J., & Alippi, C. (2020). *Deep reinforcement learning with weighted Q-Learning.* arXiv preprint arXiv:2003.09280.

Escobar, C. A. M., Pappalardo, C. M., & Guida, D. (2020). *A parametric study of a deep reinforcement learning control system applied to the swing-up problem of the cart-pole.* Applied Sciences Switzerland, 10(24), 1–19.

Gogineni, K., Dayapule, S. S., Gomez-Luna, J., Gogineni, K., Wei, P., Lan, T., Sadrosadati, M., Mutlu, O., & Venkataramani, G. (2024). *SwiftRL: Towards Efficient Reinforcement Learning on Real Processing-In-Memory Systems*. ISPASS 2024, 217–229.

Hazza, H., Ahmed, A., Fabri, S. G., Bugeja, M. K., & Camilleri, K. (2025). *Reinforcement Learning Control Strategies: Q-learning, SARSA, and Double Q-learning Performance for the Cart-Pole Problem*.2025

International Conference on Control, Automation and Diagnosis (ICCAD), pp.1-6, 2025.

Jumaah, M. A., Ali, Y. H., & Rashid, T. A. (2025). *Efficient Q-learning hyperparameter tuning using FOX optimization algorithm*. Results in Engineering, 25.

Kommey, B., Isaac, O. J., Tamakloe, E., & Opoku, D. (2024). *A Reinforcement Learning Review: Past Acts, Present Facts and Future Prospects*. Journal Research and Development (ITJRD), 8(2).

Li, P., Hao, J., Tang, H., Fu, X., Zhen, Y., & Tang, K. (2024). *Bridging evolutionary algorithms and reinforcement learning: A comprehensive survey on hybrid algorithms*. IEEE Transactions on evolutionary computation.

Manglik, A., & Tripathi, S. (2018). *Towards integrating model dynamics for sample efficient reinforcement learning*. Deep Reinforcement Learning (16-720) Project.

Mishra, S., & Arora, A. (2023). *A Huber reward function-driven deep reinforcement learning solution for cart-pole balancing problem*. Neural Computing and Applications, 35(23), 16705–16722.

Mothanna, Y., & Hewahi, N. (2022). *Review on Reinforcement Learning in CartPole Game*. 2022 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies, 3ICT 2022, 344–349.

Nagendra, S., Podila, N., Ugarakhod, R., & George, K. (2017). *Comparison of reinforcement learning algorithms applied to the cart-pole problem*. 2017 International Conference on Advances in Computing, Communications and Informatics, ICACCI 26–32.

Singh, S. P., & Sutton, R. S. 1996. *Reinforcement learning with replacing eligibility traces*. Machine Learning. 22, 123–158.

Surriani, A., Wahyunggoro, O., & Cahyadi, A. I. (2021). *Reinforcement Learning for Cart Pole Inverted Pendulum System.* IEACon IEEE Industrial Electronics and Applications Conference, 297–301.

Sutton, R. S., & Barto, A. G. (2018). *Reinforcement learning : an introduction*. The MIT Press.

Tallec, C., Blier, L., & Ollivier, Y. (2019). *Making Deep Q-learning methods robust to time discretization*. http://arxiv.org/abs/1901.09732.

Tokic, M. (2010). *Adaptive ε-greedy exploration in reinforcement learning based on value differences*. Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics),6359 LNAI,203–210.

Van Hasselt, H., Guez, A., & Silver, D. (2016, March). *Deep reinforcement learning with Double Q-learning*. The AAAI conference on artificial intelligence (Vol. 30, No. 1).

Wang, Y. H., Li, T. H. S., & Lin, C. J. (2013). *Backward Q-learning: The combination of Sarsa algorithm and Q-learning*. Engineering Applications of Artificial Intelligence, 26(9), 2184–2193.

Watkins, C. J. C. H., & Dayan, P. (1992). *Q-Learning,* Machine Learning, 8(3), 279-292.

Zhong, L. (2024). Comparison of Q-learning and SARSA Reinforcement Learning Models on Cliff Walking Problem (pp. 207–213).