

Dissecting ADDQN: An Ablation Study for Deadline-Aware Task Scheduling in Fog Computing

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Research Article

Keywords:

Posted Date: September 19th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11071902/v1>

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Additional Declarations: The authors declare no competing interests.

Abstract

This paper presents a systematic ablation study of the Attention-Enhanced Double Deep Q-Network (ADDQN) for deadline-aware task scheduling in a heterogeneous fog computing environment. Although the original ADDQN incorporates attention-based aggregation, Double DQN learning, dual-path feature processing, and a shaped multi-objective reward, the impact of each component on the overall performance of the final scheduling has not been adequately studied. In order to fill this gap, four variations of ablation are studied, namely, ADDQN without attention, ADDQN without Double DQN, ADDQN without reward shaping, and a single-path variant without dual-path fusion. Each variant is trained and tested in a homogeneous fog environment (15 fog nodes) using the same experimental protocol (500 training episodes, 200 scheduling steps/episode, 30 independent evaluation runs). The overall performance of the full ADDQN is the best, with an average response time of 136.33 ± 3.03 ms, a deadline miss ratio of 4.2 ± 0.9 , and a deadline met ratio of 95.7 ± 0.9 . The findings indicate that deleting attention or Double DQN performance suffers by a moderate degree; simplifying the reward function suffers by a bigger degree; and deleting the dual-path fusion suffers by a disastrous performance drop. In general, the results reveal that ADDQN's performance results from the interplay of several design decisions and is not limited to a single aspect, with reward shaping and dual-path fusion being the most significant contributors to robust, deadline-conscious scheduling in fog computing.

Introduction

Fog and edge computing are viable alternatives to centralized cloud processing due to the sharp rise in demand for low-latency, deadline-sensitive computing services driven by the Internet of Things (IoT) 's explosive expansion. Unlike the typical cloud environment, fog computing systems are dynamic and heterogeneous, in which processing power, queue times, network delays, and available power resources are not constant or uniform across computing nodes [1]. These features make scheduling of tasks a complex multi-objective optimization problem. It is of special importance to real-time applications requiring reliable Quality of Service (QoS) guarantees in a distributed environment and strict deadline requirements.

Classical scheduling techniques, such as latency-based, shortest-queue, and other rule-of-thumb approaches, remain widely used for their simplicity and low overhead. Nevertheless, these approaches are not always effective in the simultaneous optimization of multiple conflicting goals in the highly dynamic fog computing environments. When deploying a system in practice, a scheduler should optimize the response time, meet task deadlines, avoid node overloads, balance the use of resources, and be energy efficient. These conflicting needs cannot be easily handled by static or single-rule policies, especially in diverse, time-dependent fog and edge infrastructures [2].

Recent work has also focused more on deep reinforcement learning (DRL) to address these limitations in adaptive scheduling of tasks in edge, fog, and cloud-fog computing systems. Because they can dynamically adapt to stochastic, time-varying workload conditions and directly learn decision-making

techniques through interaction with the environment, DRL-based schedulers are particularly intriguing. Existing research indicates that DRL techniques can achieve better trade-offs among Quality of Service (QoS) objectives, improve load balancing, and reduce response time compared to standard heuristic baselines. However, many existing approaches rely on simplistic state representations, optimize only a fraction of the scheduling objectives, or do not explicitly incorporate deadline-aware scheduling in highly dynamic and heterogeneous fog scenarios [3].

The lack of component-level analysis in DRL-based fog schedulers is another drawback of the current literature. While many advanced design choices, such as Double DQN learning [1], self-attention mechanisms [2], node-feature encoding [3], and shaped multi-objective reward functions [4], are often combined in recent architectures, the current evaluation paradigm concentrates on end-to-end performance comparisons against heuristic baselines without separating the contribution of individual components. Thus, it remains ambiguous as to whether the realized benefits are primarily attributable to the better incentive engineering [4], richer state aggregation [2], more valid Q-value estimate [1] or the synergistic effects of these design choices. Since architectural complexity in systems with DRL must be empirically motivated, i.e., components that do not contribute distinctly to measured performance benefits to the system must not be introduced at the cost of unnecessary computing cost and hinder the interpretability of the model, this uncertainty is unacceptable [5], [6]. A more general methodological device for answering such questions, used throughout the machine learning literature, is the ablation study, which sequentially removes or simplifies components under controlled conditions [7]. Nevertheless, they are yet to be utilized to a significant degree in DRL-based fog scheduling frameworks.

To address this gap, this publication proposes a controlled ablation study of the Attention-Enhanced Double Deep Q-Network (ADDQN) for scheduling deadlines in a fog computing task. The research is based on the full ADDQN reference model and is conducted systematically by removing one important element at a time to quantify its contribution to performance, rather than creating a new scheduler. Specifically, under a single experimental protocol, the impacts of dual-path fusion, reward shaping, attentiveness, and Double DQN learning are investigated. The aim of this component-wise analysis is to explain the design choices that most affect minimizing reaction time and deadline breaches across a variety of fog environments.

The main contributions of this work are the following:

1. 1. A controlled ablation framework is developed in order to study the significance of critical ADDQN elements in deadline-conscious fog scheduling.
2. 2. The same training technique and environment are used to assess the individual impacts of reward shaping, dual-path fusion, Double DQN learning, and attentiveness.
3. 3. The effect of every design choice on reaction time, deadline satisfaction, and deadline ratio is all quantitatively illustrated.
4. 4. Informative design lessons are learned on how to design efficient DRL-based fog schedulers with a balance between performance of scheduling and architecture complexity.

This paper is divided into the following. Section II discusses the related work. In Section III, the ablation methodology and the experimental design are mentioned. The results of the component-wise analysis are discussed in Section IV. Lastly, the paper concludes with Section V, which outlines future directions.

Related Work

A. Fog and Edge Task Scheduling

Task scheduling has attracted considerable attention in fog and edge computing due to the dynamic, diverse, and latency-sensitive nature of IoT workloads. Delay, heterogeneity of nodes, resource variability and processing efficiency in such environments explain scheduling decisions [1]-[4]. The existing research posits that the classical, heuristic and metaheuristic models are still applicable in the task scheduling due to their simplicity and reduced complexity of computation. Nonetheless, these approaches are highly constrained in responding to evolving network characteristics and workloads because they use a fixed decision-making approach [1], [2], [4]. The limitations must be overcome in real-life, deadline-conscious scenarios, where scheduling errors can directly impact QoS adherence and service reliability.

B. DRL-Based Scheduling in Fog and Cloud–Fog Systems

Recent research has treated Deep Reinforcement Learning (DRL) as a promising approach to addressing these shortcomings and aiding adaptive task scheduling in a fog computing system. Wang et al. [5] emphasized the applicability of DRL to dynamic conditions, demonstrating its ability to improve load balancing and reaction time. On the same note, Choppara and Mangalampalli illustrate that DEL proves beneficial in the presence of various resources and workloads by introducing a DRL-based multi-objective cloud-fog system scheduler [6]. Applications Research into different areas has generalized DRA-based scheduling to edge-cloud and cloud environments, with further analysis of energy, time, and bi-objective optimization. [7], [8].

C. Double DQN, Reward Shaping, and Attention Mechanisms

This has been furthered by the introduction of advanced methods that improve the effectiveness of DRA in complex decision-making processes. One of them was Double DQN, which was developed to enhance value-based learning and reduce Q-value overestimation; this is particularly important in scheduling scenarios that require reliable decisions [9]. Reward shaping is another mechanism that has been seriously considered to guide policy optimization and is known to be an effective way to hasten convergence [10]. Additionally, attention methods have proven very promising for computation offloading and resource allocation. Such mechanisms enable models to focus on the most significant features of the input state rather than treating all features equally [11]. On a larger scale, initial studies of DRA have demonstrated the significance of learning deep representations for high-dimensional sequential optimization problems [12], [13]. The literature on fog scheduling, however, does not investigate the extent to which each of these design factors contributes to the final outcomes when implemented within a single scheduling framework.

D. Position of the Present Work

Past research was aimed at creating a complete DRL scheduler and comparing it with a heuristic baseline. The research further investigates the DRL scheduler by experimenting with it at the component level. This paper examines specific design choices within the ADDQN reference framework that are chiefly responsible for its performance, rather than simply inquiring whether a learning-based scheduler is more effective than traditional methods. This perspective is critical for identifying key elements, reducing architectural complexity, and developing the next generation of DRL-based schedulers across a variety of fog settings. Thus, by providing a controlled ablation of attention, Double DQN learning, reward shaping, and dual-path fusion within a single deadline-aware scheduling system, this paper contributes to previous research on scheduling.

Reference ADDQN Framework and Ablation Methodology

3.1 Reference ADDQN Framework

The current work is based on an existing ADDQN reference framework for deadline-sensitive fog scheduling and a controlled, component-based ablation analysis [19]. In our work, the complete Attention-Enhanced Double Deep Q-Network (ADDQN) is used as a model of scheduling architecture. The reference model is based on deadline-constrained task scheduling in a heterogeneous fog computing environment, where each incoming task must be allocated to one of the existing fog nodes under dynamic resource constraints. The current work builds on the full ADDQN as a reference model and explores the role of its key components through controlled ablation, rather than proposing a new scheduler.

The scheduling problem is formulated as a Markov Decision Process (MDP). The system state comprises the state of all fog nodes at each decision step. Precisely, the environment comprises 15 fog nodes, and each node has five normalized features: CPU utilization, queue length, latency, remaining energy, and capacity factor. In this manner, the state vector is 75-dimensional. The space of actions is to choose one of the 15 fog node options to handle the incoming task.

The first step implemented by the reference ADDQN is to apply a node encoder that converts the original node features into a more informative embedding space. Such embeddings are subsequently subjected to an attention mechanism, which learns the relative significance of nodes at the current scheduling step and generates a global context representation. The model requires a dual-path design that has a global-context path and a node-level path to enable global and fine-grained decision-making. The products of these two routes are combined and fed to a Q-value head, which predicts a single Q-value to each candidate fog node.

The learning reference frame is based on the Double DQN paradigm, in which action selection and appraisal are decoupled to eliminate overestimation of Q-values and enhance training stability. Its initial

version also uses Adam, replay-buffer training, target-network synchronization, gradient clipping, and an ϵ -greedy exploration policy in 500 training episodes.

The reference model has a multi-objective and shaped reward design. It collectively considers the deadline, response-time reduction, overload elimination, load balancing, and energy-conscious scheduling. Of these elements, deadline satisfaction receives the most attention, reflecting the scheduler's deadline-consciousness. The complete ADDQN is the reference configuration in this paper, which is compared with all ablation variants.

3.2 Ablation Study Design

Although the ADDQN reference demonstrates good results for deadline-aware fog scheduling, the end-to-end behavior is driven by several interacting architectural and learning components. This means that the input of individual components cannot be directly inferred from the performance of the entire model. Specifically, the extent to which the ultimate improvement can be attributed to the attention mechanism, the Double DQN update rule, the shaped reward formulation, or the dual-path fusion design is unclear.

To overcome this problem, the current research uses a controlled one-factor-at-a-time ablation approach. In both types of ablation, a key element of the reference ADDQN is eliminated or reduced, while the remaining elements and the entire experimental environment are kept as intact as possible. This design allows the contribution of each component to be measured in relative terms without confounding modifications to the other components of the framework.

Each ablation variant is trained and tested using the same experimental protocol as the reference model. The environmental dynamics, the number of nodes, the node features, and the number of fog nodes remain the same, as does the task-generation process. Similarly, each variant to be tested has 500 training episodes (200 decision steps per episode) and is evaluated in 30 independent runs using the same performance measures. Such a controlled condition is required to ensure that the observed differences in performance are primarily due to the removed part rather than to other implementation or training differences. To make a comparison with the original study, the external baselines applied in the original study, which are the Shortest Queue, Lowest Latency, and Random scheduling, are also maintained.

3.3 ADDQN w/o Attention

A no-attention variant of the reference ADDQN is made in order to assess the role of the attention mechanism. In this modification, the learned attention layer is removed without altering the rest of the original structure, including the node encoder, the two-way processing architecture, the Double DQN learning algorithm, and the shaped multi-objective reward.

The model does not compute adaptive node-importance weights; instead, it computes an aggregate node embedding using a fixed, non-learned operation. More precisely, the representations of the global context are obtained by performing mean pooling over the encoded node features. The resultant context vector is then passed through the identical global processing branch, and the node-level branch processes the flattened node embeddings, followed by feature fusion and Q-value prediction.

The aim of this ablation is to determine whether learned attention plays a significant role in identifying the most relevant node states under heterogeneous fog-propagated conditions, or whether an unrestricted, non-learned aggregation approach can be used effectively to schedule with respect to deadlines.

3.4 ADDQN w/o Double DQN

In an effort to assess the value of the Double DQN learning mechanism, a no-DDQN variant is developed where the network architecture remains the same, consisting of the node encoder, attention mechanism, dual-path design, and shaped reward function. The sole change is inserted in the computation of the Q-learning target.

This variant uses the standard DQN target (the maximum Q-value predicted by the target network) rather than the Double DQN target formulation, in which action selection is made by the policy network and action evaluation by the target network. This ablation removes the particular contribution of stable value estimation to deadline-aware fog scheduling by keeping all other elements of the reference framework constant.

This variant aims to determine whether the performance of the reference ADDQN relies heavily on the stabilization provided by Double DQN, or whether similar results can be attained by applying a conventional DQN-like learning rule.

3.5 ADDQN w/o Reward Shaping

A no-reward-shaping version is built in which the network architecture and learning scheme are maintained, comprising the node encoder, attention mechanism, dual-path processing structure, and Double DQN training procedure.

Only the deadline-related and reaction-time aspects are retained in the simplified reward, whereas the full-shaped reward jointly accounts for deadline satisfaction, response time, overload avoidance, load balancing, and energy-aware scheduling. This architecture enables a controlled evaluation of whether the reference model's richer reward engineering is a significant source of scheduling improvement.

This ablation aims to determine whether a more straightforward reward that solely considers deadlines and latency is sufficient to achieve excellent deadline-aware scheduling performance, or whether the full

ADDQN requires multi-objective reward shaping.

3.6 ADDQN w/o Dual-Path Fusion (Single-Path Variant)

The mentioned ADDQN framework was used to build a single-path version to evaluate the contribution of the dual-path fusion mechanism. In this version, the model was tested to rely on the global context path, so the node encoder, the attention mechanism, and the Double DQN learning procedure are preserved, but there is no node-level processing branch, and the feature-fusion stage is removed.

The node-level path in the reference ADDQN maintains fine-grained structural information before final action-value prediction, while the global path captures a compact, high-level representation of the system state. The output of the global-context path is directly connected to the Q-value head in the current ablation, eliminating the node-level branch and combiner. While maintaining the integrity of the other elements, this design separates the function of representation fusion.

This ablation verifies that for optimal scheduling decisions, it is important to combine global and node-level information. However, in deadline-aware fog situations, a simpler single-path design can deliver equivalent performance.

Results and Discussion

4.1 Effect of Removing Attention

The final analysis of the no-attention variant, based on 30 independent runs, is summarized in Table 1. The No-Attention ADDQN achieved an average response time of 145.64 ± 6.59 ms, a deadline-miss ratio of $11.7\% \pm 6.1\%$, and a deadline-met ratio of $88.3\% \pm 6.1\%$. In comparison, the full ADDQN reference model achieved 136.33 ± 3.03 ms, $4.2\% \pm 0.9\%$, and $95.7\% \pm 0.9\%$, respectively. Thus, eliminating the attention mechanism led to the following results: response time increased by about 6.8%, the deadline-miss ratio increased by nearly 179%, and deadline satisfaction decreased by about 7.4%. These findings suggest that the attention mechanism plays a valuable role in the effectiveness of the entire ADDQN architecture.

Despite this degradation relative to the full model, the no-attention variant nonetheless achieved better performance in several aspects than the heuristic baselines. It decreased the average response time relative to Shortest Queue by 154.23 ms, to 145.64 ms, and the deadline-miss ratio by 19.5%, to 11.7%. It also did better than Random scheduling, which had a 157.51 ms response time and 21.8% deadline-miss ratio. These findings indicate that the other parts of the framework may continue to play an efficient role in scheduling, whereas the learned attention mechanism adds value by enabling the model to better pinpoint the most pertinent node information when making decisions.

Attention contributes in a way that is especially noticeable in deadline-sensitive behavior. Whereas the decline in mean response time is modest, the increase in missed deadlines is significantly greater. This means that, in addition to decreasing latency, attention increases the scheduler's sensitivity to node states that are vital for preventing deadline violations under heterogeneous, dynamically congested fog conditions. Hence, the full ADDQN can make more deadline-aware assignments than a variant based on uniform aggregation.

The dynamics of training in the no-attention case are depicted in Fig. 2. The curves indicate that the model continues to learn a useful scheduling policy, but its convergence is noisier and less stable than that of the full ADDQN. This finding is consistent with the increased run-to-run variance in the no-attention condition, where the standard deviation of response time (6.59 ms) is significantly greater than that of the complete model (3.03 ms). Altogether, these results allow us to conclude that attention is not just a secondary aspect but a valuable process that can enhance the performance and robustness of deadline-conscious fog scheduling.

Altogether, the outcomes of this ablation indicate that the attention mechanism is not a trivial factor in ADDQN's success. The no-attention variant remains competitive with classical scheduling heuristics, but the full ADDQN clearly has the advantage of attention, especially in minimizing deadline violations and improving performance consistency across runs. The significant increase in the deadline-miss ratio when attention is removed indicates that adaptive node weighting is particularly important in deadline-conscious scheduling, even when the other ADDQN elements are kept.

Table 1
Performance of the no-attention ablation variant.

Method	Avg. Response Time (ms)	Deadline Miss Ratio (%)	Deadline Met Ratio (%)
Full ADDQN	136.33 ± 3.03	4.2 ± 0.9	95.7 ± 0.9
No-Attention ADDQN	145.64 ± 6.59	11.7 ± 6.1	88.3 ± 6.1
Shortest Queue	154.23 ± 9.82	19.5 ± 8.6	80.5 ± 8.6
Random	157.51 ± 5.12	21.8 ± 4.3	78.2 ± 4.3
Lowest Latency	441.36 ± 261.97	60.6 ± 17.2	39.4 ± 17.2

4.2 Effect of Removing Double DQN

Table 2 reveals that the performance of the DDouble DQN learning mechanism is evident. It degrades when the Double DQN is removed compared to the full ADDQN reference model. According to the summary of the 30-run evaluation, the No-DDQN ADDQN had an average response time of 146.52 ms with a standard deviation of 7.62 ms, a deadline miss rate of 12.5%, and a deadline met rate of 87.5%. In contrast, the full ADDQN achieved 136.33 ± 3.03 ms, 4.2% ± 0.9%, and 95.7% ± 0.9%, respectively. This

translates to a response time improvement of about 7.5%, a nearly 198% improvement in the deadline miss ratio, and a decrease of about 8.2% in deadline satisfaction upon eliminating Double DQN.

Despite not performing as well as the full ADDQN, the no-ddqn variant still performed better in some respects compared to the heuristic baselines. The no-DDQN model still had a better response time and fewer deadline violations than Shortest Queue, which had a response time of 154.23 ± 9.82 ms and a deadline miss ratio of $19.5\% \pm 8.6\%$. It also performed better than Random scheduling, resulting in a response time of 157.52 ± 5.40 ms and a $22.2\% \pm 4.0\%$ ratio of deadline misses. These results suggest that the general ADDQN framework remains useful in the absence of Double DQN, but that the significant difference between the final scheduler quality and the full model indicates that learning stability is a key factor in determining the quality of the final scheduler.

Deadline-related behavior is the most affected by the elimination of Double DQN. Although the average response time growth is moderate, the growth in the deadline miss ratio is quite significant. This indicates that not only do unstable or exaggerated Q-values degrade latency, but they also reduce the scheduler's ability to reliably choose deadline-safe assignments under dynamic fog conditions. In time-constrained systems, a relative instability in value estimation can lead to suboptimal node-selection decisions, with compounding effects on the number of missed deadlines.

The other notable observation concerns robustness. The response time of the no-DDQN model (7.62 ms) is much larger than that of the full ADDQN (3.03 ms), and the same is true of the deadline variability. This means that not only does eliminating Double DQN reduce average performance, but it also increases the scheduler's unevenness in independent runs. In summary, the significant increase in the deadline miss ratio when using a Double DQN target is mitigated by replacing it with a standard DQN target, demonstrating that stable value estimation is critical for deadline-aware fog scheduling.

Table 2
Performance of the no-DDQN ablation variant.

Method	Avg. Response Time (ms)	Deadline Miss Ratio (%)	Deadline Met Ratio (%)
Full ADDQN	136.33 ± 3.03	4.2 ± 0.9	95.7 ± 0.9
No-DDQN ADDQN	146.52 ± 7.62	12.5 ± 6.1	87.5 ± 6.1
Shortest Queue	154.23 ± 9.82	19.5 ± 8.6	80.5 ± 8.6
Random	157.52 ± 5.40	22.2 ± 4.0	77.8 ± 4.0
Lowest Latency	441.36 ± 261.97	60.6 ± 17.2	39.4 ± 17.2

In general, this ablation confirms that Double DQN is not just a training refinement, but a fundamental component of the stability, robustness, and deadline-conscious performance of the entire ADDQN scheduler.

4.3 Effect of Removing Reward Shaping

The performance of the no-reward-shaping variant is summarised in Table 3. It can be seen that removing the full reward-shaping design results in a significant deterioration of performance when compared to the full ADDQN reference model. According to the 30-run analysis, the No-Reward-Shaping ADDQN had an average response time of $151.05 \text{ ms} \pm 9.25 \text{ ms}$, a deadline miss ratio of $16.8\text{--}7.7\%$, and a deadline met ratio of $83.2\text{--}7.7\%$. In comparison, the full ADDQN achieved $136.33 \pm 3.03 \text{ ms}$, $4.2\% \pm 0.9\%$, and $95.7\% \pm 0.9\%$, respectively. This is equivalent to a 10.8% change in response time, a 301% change in the deadline miss ratio, and a 12.5% change in deadline satisfaction.

The no-reward-shaping variant did not perform as well as the full ADDQN, but it still did slightly better than some heuristic baselines. The no-reward-shaping model resulted in a lower response time and a lower deadline violation as compared to Shortest Queue, which had a response time of $154.23 \pm 9.82 \text{ ms}$ and a deadline violation rate of $19.5\% \pm 8.6\%$. It also compared better with Random scheduling, which had a response time of $157.65 \pm 5.05 \text{ ms}$ and a %age of defaulting on the deadline of $22.4\% \pm 4.3\%$. But the margin over these baselines was significantly smaller than in the full model, suggesting that a substantial portion of ADDQN's advantage stems from the more reward-rich design that drives learning toward more general QoS-conscious behavior.

The impact of eliminating reward shaping is especially noticeable in deadline-sensitive performance. Though the average response time is increasing, the change in the ratio of deadline misses is quite significant. This implies that the entire reward function is not just an enhancement of latency. It also guides the planner to make choices that prevent overloaded nodes, promote better resource utilization, and minimize future congestion that can lead to deadline misses. If these other reward terms are removed, the agent will still be able to optimize immediate deadline and response-time goals, but it will no longer receive explicit information about the larger system's health and the stability of long-term schedules.

The other notable observation concerns robustness. The standard deviation of response time in the no-reward-shaping model (9.25 ms) is significantly larger than that of full ADDQN (3.03 ms), and the same trend is reflected in variability with the deadline. This implies that not only is the average quality of the learned policy enhanced by reward shaping, but its consistency is also improved when learning is repeated. Altogether, the significant decline following the simplification of the rewarding role indicates that multi-objective reward shaping is necessary to inform efficient, deadline-conscious scheduling choices beyond mere latency and deadline optimization.

Table 3
Performance of the no-reward-shaping ablation variant.

Method	Avg. Response Time (ms)	Deadline Miss Ratio (%)	Deadline Met Ratio (%)
Full ADDQN	136.33 ± 3.03	4.2 ± 0.9	95.7 ± 0.9
No-Reward-Shaping ADDQN	151.05 ± 9.25	16.8 ± 7.7	83.2 ± 7.7
Shortest Queue	154.23 ± 9.82	19.5 ± 8.6	80.5 ± 8.6
Random	157.65 ± 5.05	22.4 ± 4.3	77.6 ± 4.3
Lowest Latency	441.36 ± 261.97	60.6 ± 17.2	39.4 ± 17.2

4.4 Effect of Removing Dual-Path Fusion

Table 4 shows that removing the dual-path fusion mechanism drastically degrades performance relative to the complete ADDQN reference model. The Single-Path ADDQN had a mean response time of 3220.16 ± 2017.46 ms, a deadline miss rate of $80.8\% \pm 25.5$, and a deadline met rate of $19.2\% \pm 25.5$ across over 30 independent evaluation runs. In contrast, the full ADDQN achieved 136.33 ± 3.03 ms, $4.2\% \pm 0.9\%$, and $95.7\% \pm 0.9\%$, respectively. This translates to a response time increase of about 2,262%, a deadline miss ratio increase of about 1,824%, and a decrease in deadline satisfaction of about 76.5% points. These findings reveal that dual-path fusion is an important element of the ADDQN framework.

The single-path variant was much inferior to the heuristic baselines. Compared to the 154.23 ± 9.82 ms response time and $19.5\% \pm 8.6\%$ deadline miss ratio of Shortest Queue and 156.90 ± 4.87 ms response time and $21.6\% \pm 4.2\%$ deadline miss ratio of Random scheduling, Single-Path ADDQN generated significantly higher delay and a much higher deadline miss ratio. It also underperformed the Lowest Latency baseline in the deadline miss ratio and deadline satisfaction. These results show that the global-context path alone is ineffective at facilitating successful scheduling decisions in this setting, despite maintaining attention and Double DQN learning.

The ablation is especially instructive in the context of representation learning. The global path of ADDQN provides a succinct, high-level overview of the environment, and the node-level path provides fine-grained structural information about the encoded node embeddings, then chooses the final action. Elimination of the second path forces the model to rely solely on compressed global information, which may not be sufficient to distinguish among individual fog nodes in heterogeneous, dynamically congested environments. Good deadline-conscious scheduling must thus go beyond global situational awareness to explicit node-specific detail.

The other significant observation is regarding robustness. The standard deviation of response time in the single-path (2017.46 ms) is much larger than that of the full ADDQN (3.03 ms), suggesting highly unstable dynamics across independent runs. Similarly, a large variance can also be found in deadline-related metrics. In general, the dramatic failure of the single-path variant shows that dual-path fusion is

necessary for ADDQN, as the global context alone cannot ensure credible deadline-constrained scheduling choices in heterogeneous fog settings.

Table 4
Performance of the single-path ablation variant.

Method	Avg. Response Time (ms)	Deadline Miss Ratio (%)	Deadline Met Ratio (%)
Full ADDQN	136.33 ± 3.03	4.2 ± 0.9	95.7 ± 0.9
Single-Path ADDQN	3220.16 ± 2017.46	80.8 ± 25.5	19.2 ± 25.5
Shortest Queue	154.23 ± 9.82	19.5 ± 8.6	80.5 ± 8.6
Random	156.90 ± 4.87	21.6 ± 4.2	78.4 ± 4.2
Lowest Latency	441.36 ± 261.97	60.6 ± 17.2	39.4 ± 17.2

4.5 Comparative Analysis Across Ablation Variants

An overall comparison across all ablation conditions shows that the elements of ADDQN are not equally useful for scheduling performance. Table 5 indicates that the full ADDQN had the highest overall performance with an average response time of 136.33 ± 3.03 ms, a deadline miss ratio of $4.2\% \pm 0.9$, and a deadline met ratio of $95.7\% \pm 0.9$. After the removal of individual components, performance dropped to varying degrees, suggesting that the importance of the architectural and learning elements differed. The reference ADDQN is an encoding of nodes, attention-based aggregation, dual-path feature processing, Double DQN learning, and a shaped multi-objective reward, and its good baseline performance is used to measure all ablation variants.

The removal of the attention mechanism in the moderate ablations resulted in the smallest performance reduction. The No-Attention ADDQN achieved a response time of 145.64 ± 6.59 ms, a deadline-miss ratio of $11.7\% \pm 6.1\%$, and a deadline-met ratio of $88.3\% \pm 6.1\%$. A slightly greater degradation was noted by the removal of the Double DQN learning rule, with 146.52 ± 7.62 ms, $12.5\% \pm 6.1$, and $87.5\% \pm 6.1$ in No-DDQN ADDQN. These findings indicate that stable value estimation makes a slightly larger contribution to the ultimate quality of the learned policy, but all elements remain significantly helpful.

An even greater effect was found when the shaped multi-objective reward was reduced. The No-Reward-Shaping ADDQN recorded a response time of 151.05 ± 9.25 ms, a deadline miss ratio of $16.8\% \pm 7.7\%$, and a deadline met ratio of $83.2\% \pm 7.7\%$. This degradation is greater, especially in deadline satisfaction, than in the two earlier ablations. These results imply reward shaping must not be merely a second-order expediency; it is an efficient optimization signal that helps the scheduler not only to consider immediate delays but also to take into account larger system-wide issues such as overload avoidance, load distribution and the quality of long-run schedules.

The most extreme degradation occurred in the Single-Path ADDQN form; the node-level path and feature-fusion step were removed. This model produced a response time of 3220.16 ± 2017.46 ms, a deadline miss ratio of $80.8\% \pm 25.5\%$, and only a $19.2\% \pm 25.5\%$ deadline met ratio. The single-path variant did not work at all, whereas the other ablations were at least partially competitive with heuristic baselines. This observation implies that dual-path fusion is not a fine-tuning but a necessary aspect of effective scheduling in the ADDQN framework.

Figure 3 shows the degradation of each ablation variant in comparison with the complete ADDQN. The figure agrees with the ranking suggested by the results and discussion in the table: the dual-path fusion is the most essential element, followed by reward shaping, Double DQN learning, and attention. The weakest degradation was achieved by removing attention, and the most devastating failure was by removing the node-level branch and using only a global representation.

Relative degradation of the ablation variants compared to the Full ADDQN with respect to response time, deadline miss ratio, and deadline met ratio.

In general, the comparative analysis shows that ADDQN is a truly composite architecture in which each key component makes a distinct contribution. The meaningful gains come from attention and Double DQN; reward shaping offers good optimization advice; and dual-path fusion seems inevitable. The combined ablation results thus demonstrate that ADDQN's efficacy stems from a combination of design options, with dual-path fusion and reward shaping proving the most powerful elements in deadline-conscious fog scheduling.

Table 5
Unified comparison of the Full model and ablation variants.

Method	Avg. Response Time (ms)	Deadline Miss Ratio (%)	Deadline Met Ratio (%)
Full ADDQN	136.33 ± 3.03	4.2 ± 0.9	95.7 ± 0.9
No-Attention ADDQN	145.64 ± 6.59	11.7 ± 6.1	88.3 ± 6.1
No-DDQN ADDQN	146.52 ± 7.62	12.5 ± 6.1	87.5 ± 6.1
No-Reward-Shaping ADDQN	151.05 ± 9.25	16.8 ± 7.7	83.2 ± 7.7
Single-Path ADDQN	3220.16 ± 2017.46	80.8 ± 25.5	19.2 ± 25.5

4.6 Statistical Analysis Across Ablation Variants

To further confirm the ablation results, further statistical comparisons between the Full ADDQN and each ablation variant were done using the reported 30-run summary statistics. In the same evaluation context, the Welch t-test was used to assess differences in average response time and deadline miss ratio; Cohen's d was reported as an effect size measure. Based on the statistical summary, none of the

ablation variants differs significantly from the Full ADDQN in either metric, with all comparisons having $p < 0.001$.

In response time, all ablation variants showed statistically significant degradation relative to the Full ADDQN, with large effect sizes. The largest degradation was found in the Single-Path variant, and the least in the No-DDQN and No-Attention variants. The same pattern was observed in the deadline miss ratio across all variants: a highly significant deterioration, with the Single-Path model generating by far the strongest statistical impact. These findings show that the mean values provide not only a descriptive view of degradation in the ablation study but also statistically significant evidence of degradation.

The Single-Path ablation displayed the largest statistical deviation between the Full ADDQN, and this is in perfect agreement with the comparative outcomes mentioned above. Conversely, the No-Attention and No-DDQN versions exhibited smaller (even though still substantial) effect sizes, with degradation being more moderate. The No-Reward-Shaping variant was in the middle ground, implying that reward shaping contributes more than attention and Double DQN, but not as much as dual-path fusion. In general, the statistical analysis supports the ranking order established in the ablation discussion: dual-path fusion is the most important element, followed by reward shaping, and lastly attention.

Taken together, these results provide solid statistical evidence supporting the argument that ADDQN is a truly composite architecture, with its effectiveness relying on the interplay among several design decisions. In particular, the large and very significant impact of the Single-Path variant highlights the fact that both global and node representations are instrumental in the strong deadline-aware scheduling in heterogeneous fog environments.

Table 6
Comparison between Full ADDQN and ablation conditions, statistically.

Comparison	RT t-statistic	RT p-value	RT Cohen's d	DMR t-statistic	DMR p-value	DMR Cohen's d
Full vs No-Attention	-7.03	< 0.001	1.82	-6.66	< 0.001	1.72
Full vs No-DDQN	-6.81	< 0.001	1.76	-7.37	< 0.001	1.90
Full vs No-Reward-Shaping	-8.28	< 0.001	2.14	-8.90	< 0.001	2.30
Full vs Single-Path	-8.37	< 0.001	2.16	-16.44	< 0.001	4.25

Caption note

The values are determined using the t-test of Welch, using the 30-run. All comparisons are statistically significant at $p < 0.001$.

Discussion

Ablution experiment elucidates the effectiveness of ADDQN model in the time scheduling of deadline-sensitive tasks within heterogeneous fogs. Rather than treating the performance of the reference model as the result of a single architectural design choice, the results suggest that ADDQN is indeed a highly composite framework, with different components playing different roles. By integrating the comparison of the variants, it is possible to conclude that the Full ADDQN achieves the best overall performance, and the systematic removal of the separate parts leads to stable but non-uniform deterioration. This indicates that the success of this model is due to the product of representation learning, learning stability, and reward design, rather than independent enhancements.

The first unexpected finding is that attention is not the predominant factor but a major contributor to the scheduler's final quality. Attention elimination was the least affected by the ablations considered, suggesting that adaptive node weighting assists the model to pay attention to significant node states, especially in time-sensitive decisions, but does not, by itself, determine the overall performance of the framework. Practically, the remaining architecture remains scheduling-performing, attention-free, indicating that attention is more of an enhancement mechanism (performance) than a structural necessity for ADDQN.

The two outcomes are that the contribution of Double DQN learning is superior to that of attention, mainly due to its stability in value estimation. The No-DDQN variant was also competitive with the heuristic policies, however, a higher miss rate in the deadline and a larger variance suggest that the only value that can be estimated reliably to obtain reliable deadline-conscious scheduling is the stable one. This finding is in line with the initial intention of using Double DQN in the reference architecture, i.e., minimizing Q-value overestimation and enhancing training stability in sequential decision-making problems. By doing so, the role of Double DQN in ADDQN is not merely to enhance the algorithm, but to ensure the high quality of the policy in a dynamic and misty environment.

The third and most significant outcome is associated with reward shaping. The simplification of the reward function resulted in the most degraded one as compared to both attention removal and Double DQN removal, particularly in deadline satisfaction. This shows that the good performance of ADDQN cannot be explained just by the network architecture; the quality of the optimization signal during learning is also a factor. This entire reward scheme is explicitly a combination of deadline satisfaction, response time, overload avoidance, load balancing, and energy-minded behavior, and as a consequence, the scheduler is now motivated to learn policies that not only make decisions with immediate payoffs but also with healthier systemwide payoffs. After simplifying this richer signal, the learned policy is significantly weaker and less stable, despite no change to the model's architecture.

The most significant study conclusion is the impact of eliminating a dual-path fusion. The Single-Path model of ablation suffered a catastrophic collapse across all ablation variants, as both response time and deadline-related behavior deteriorated severely. This finding is a solid indication that ADDQN's success is rooted in the ability to blend two mutually exclusive views: a small global-context representation and an explicitly detailed view of nodes. The global path alone does not seem sufficient

to differentiate among individual fog nodes under heterogeneous, dynamically congested conditions. As such, dual-path fusion is not a frivolous architectural optimization but a mechanism for representation learning that is necessary for the scheduler to maintain system-wide awareness and node-specific discrimination.

These interpretations are further supported by the statistical analysis. The average response time and the deadline miss ratio for all ablation variants differed significantly from those of Full ADDQN, and all comparisons were $p < 0.001$. In addition, the Cohen d values reported are large across all variants, with the most significant effect observed in the Single-Path model. These findings prove that the degradations are not only descriptive differences in averages, but statistically significant changes in scheduler behavior. In this regard, the study not only ranks the components qualitatively but also provides quantitative support for their relative significance.

In a more general design, the results indicate that, to achieve high-quality fog scheduling in deadline-conscious environments, a strong DRL backbone alone is insufficient. The scheduler has to: 1) maintain information state representations, 2) maintain fixed-point learning dynamics, and 3) be rewarded in a way that is sensitive to the multi-objective nature of the problem. The ablation results indicate that weakening any of these factors is detrimental to performance, though weakening the representation fusion is particularly devastating. It renders the current study valuable not just as a validation of ADDQN, but also as a collection of useful design principles for future DRL-based fog schedulers.

Lastly, and importantly, another valuable scientific aspect of the work is brought to light in the discussion: why the initial framework is effective. The previous ADDQN experiment confirmed that the complete model is superior to heuristic baselines and demonstrates good deadline awareness when using the adopted protocols. The current paper augments this contribution by demonstrating that the gains are not evenly shared among the model's components, with dual-path fusion and reward shaping proving to be the most significant design options. Such component-based knowledge makes the framework more interpretable and provides a more rigorous foundation for the further development of the architecture.

Conclusion

The paper presented a controlled ablation study on the Attention-Enhanced Double Deep Q-Network (ADDQN) for scheduling deadline-aware tasks in heterogeneous computing using MISTs. The paper did not introduce a new scheduler but instead investigated the relative significance of four key components of the reference framework: attention, Double DQN learning, shaped multi-objective reward design, and dual-path fusion. The research measured the effect of each design decision on the quality of the schedule by removing a single component of the architecture and holding the evaluation protocol constant. These findings indicate that the Full ADDQN achieves the highest overall performance, with an average response time of 136.33 ± 3.03 ms, a deadline miss ratio of $4.2\% \pm 0.9\%$, and a deadline met ratio of $95.7\% \pm 0.9\%$. Attention removal resulted in the least significant degradation; removing Double

DQN led to a slightly larger drop; and simplifying the reward function led to a more significant performance drop. The worst failure was achieved by eliminating the dual-path fusion, in which the Single-path type failed catastrophically on response time and deadline-related behavior. The results determine the following practical priorities for component significance in this context: dual-path fusion, reward shaping, Double DQN learning, and attention.

The same conclusion is supported by the statistical analysis. Each ablation variant showed a significant difference in response time and deadline miss ratio, with all comparisons having p-values < 0.001 and significant effect sizes. The most significant statistical impact was observed for the Single-Path variant, demonstrating that, to make sound scheduling decisions in the context of heterogeneous mogs, it is important to maintain both global and node-level representations.

On the whole, the paper demonstrates that ADDQN is a truly composite architecture in which the effectiveness of different design decisions is achieved through their cooperation, rather than by any single component in isolation. Specifically, the results indicate that dual-path fusion is necessary to achieve the desired quality of representations, and that reward shaping is necessary to guide the scheduler toward more QoS-aware behavior beyond immediate latency optimization. In this regard, the current paper not only confirms the ADDQN framework as a reference but also offers valuable design insights for future DRL-based fog schedulers operating in deadline-sensitive, resource-constrained environments.

The framework can be expanded to explore how the identified component hierarchy can be maintained in larger, more realistic fog environments, under non-stationary task-arrival patterns, with alternative state representations, or in distributed and multi-agent scheduling environments, as a future direction. These extensions would help determine whether the significance of fusion, reward shaping, and learning stability extends beyond the current experimental setup.

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Figures

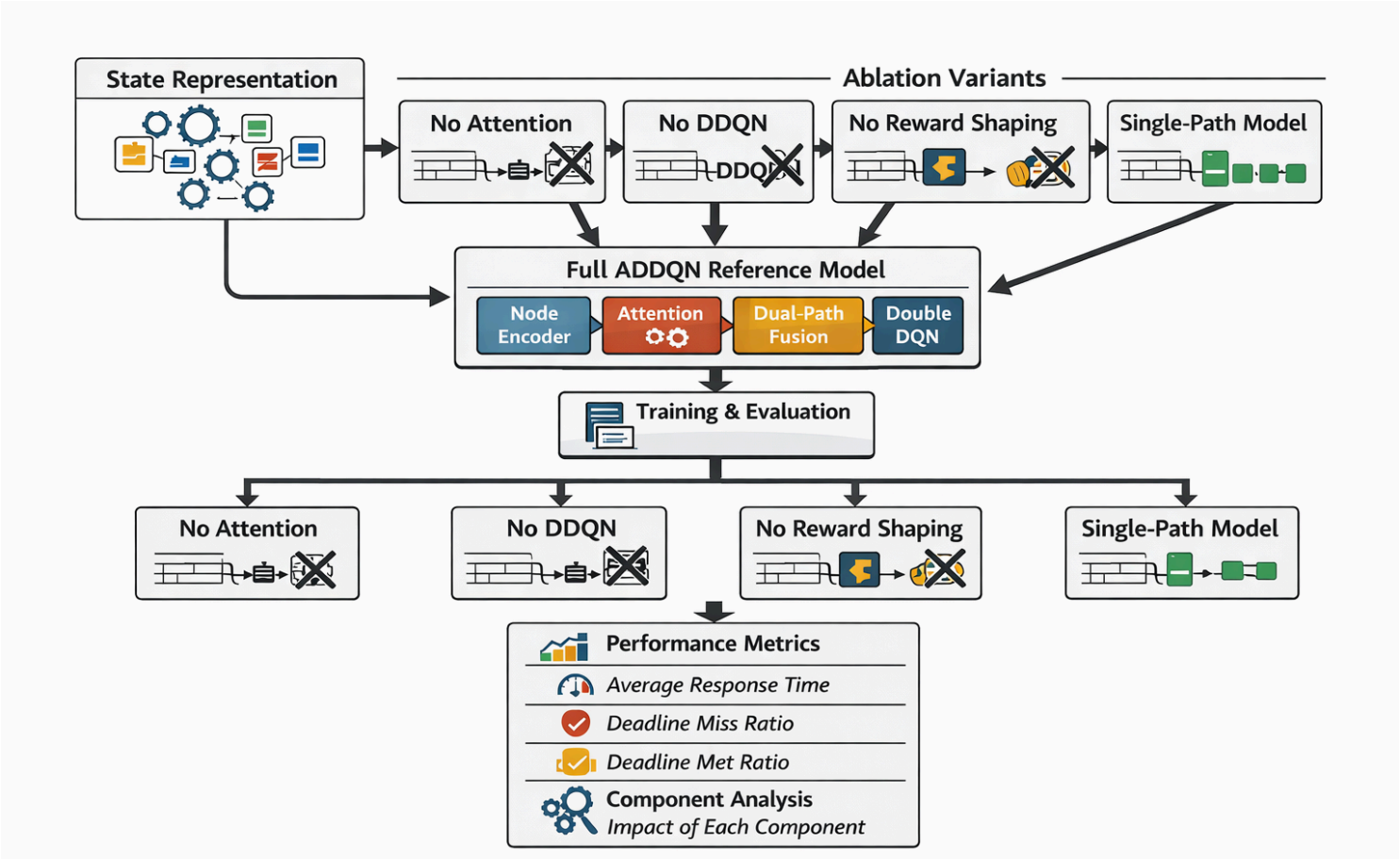


Figure 1

Overview of the reference ADDQN framework, the evaluated ablation variants, and the common training and evaluation pipeline used for component-wise analysis.

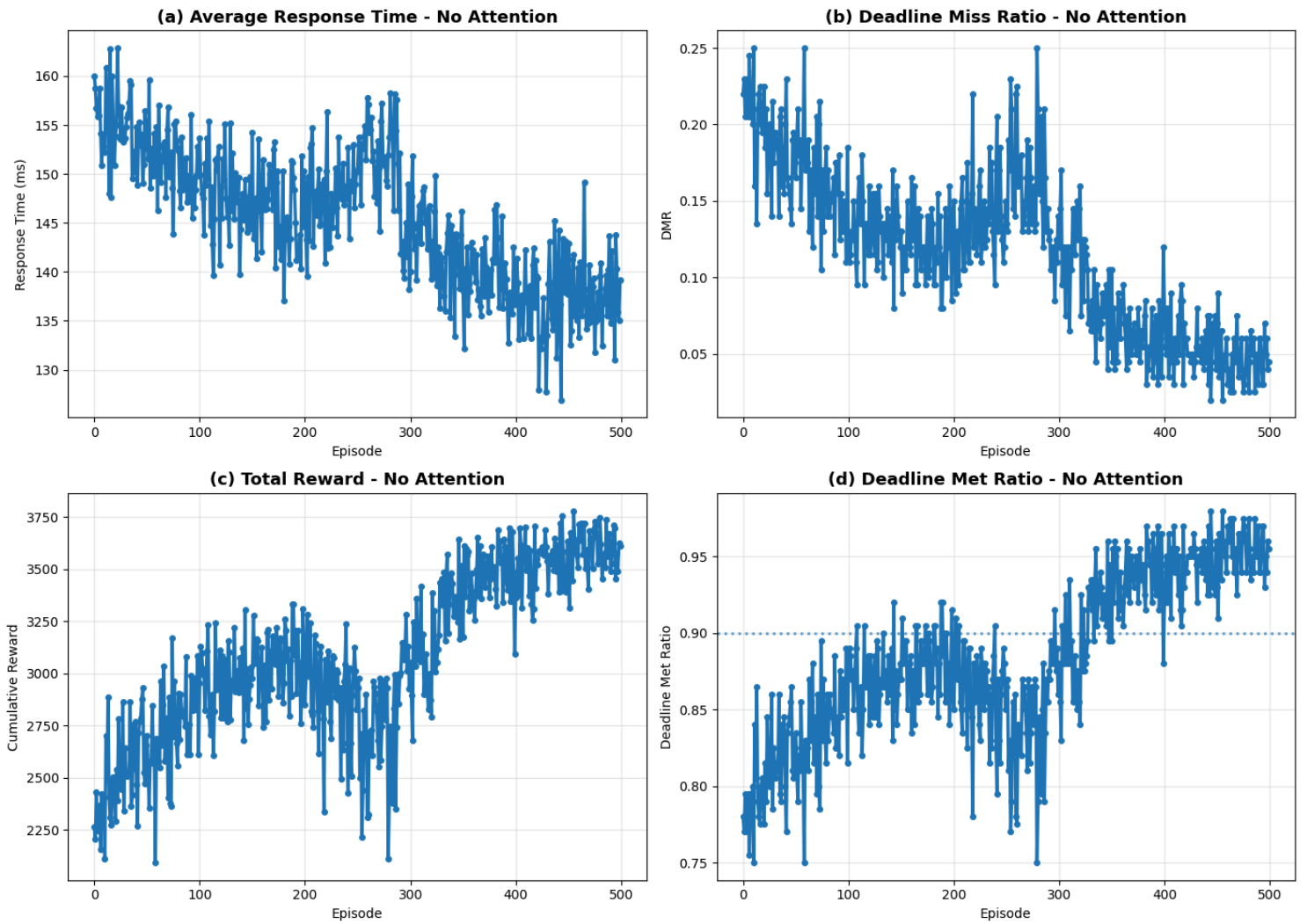


Figure 2

Training dynamics of the no-attention ablation variant.

Training curves for the no-attention variant, including response time, deadline miss ratio, cumulative reward, and deadline met ratio.

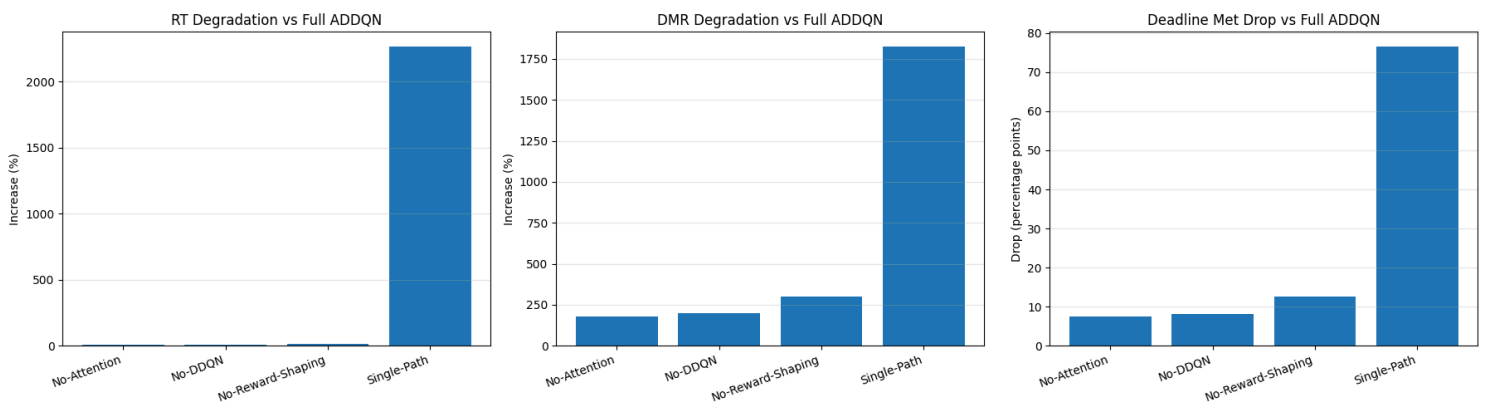


Figure 3

Relative degradation of each ablation variant with respect to the Full ADDQN for response time, deadline miss ratio, and deadline met ratio.