Review of Deep Reinforcement Learning for Offshore Wind Farm Maintenance Planning

Marco Borsotti, Xiaoli Jiang, and Rudy R. Negenborn

Department of Maritime & Transport Technology, Delft University of Technology, Delft, Netherlands

Correspondence: Marco Borsotti (m.borsotti@tudelft.nl)

Abstract. Offshore wind farms face unique challenges in maintenance due to harsh weather, remote locations, and complex logistics. Traditional maintenance strategies often fail to optimize operations, leading to unplanned failures or unnecessary servicing. In recent years, Deep Reinforcement Learning (DRL) has shown clear potential to tackle these challenges through a data-driven approach. This paper provides a critical review of representative DRL models for offshore wind farm maintenance
5 planning, elaborating on both single- and multi-agent frameworks, diverse training algorithms, various problem formulations, and the integration of domain-specific knowledge. The review compares the benefits and limitations of these methods, identifying a significant gap in the widely adopted use of simplistic binary maintenance decisions, rather than including multi-level or imperfect repairs in the action space. This work finally suggests directions for future research, to overcome current limitations and enhance the applicability of DRL methods in offshore wind maintenance.

1 Introduction

10 Offshore wind farm maintenance presents unique challenges due to harsh weather conditions, remote locations, and the intricate coordination of logistical resources (National Renewable Energy Laboratory, 2022). Storms, high winds, and unpredictable sea states create uncertainty in scheduling, while the limited accessibility of offshore sites further complicates intervention planning. Additionally, the need to allocate maintenance crews, vessels, and spare parts efficiently increases operational complexity, often leading to delays and higher costs. Traditional maintenance strategies such as corrective or scheduled preventive, struggle
15 to mitigate these challenges, often resulting in unplanned failures or unnecessary servicing (Fox et al., 2022).

In recent years, DRL has shown promising results as a data-driven approach to tackle these challenges. DRL is a class of algorithms that combine the sequential decision-making framework of reinforcement learning (RL) with the representational power of deep neural networks. In a typical RL setting, an agent interacts with an environment defined as a Markov Decision
20 Process (MDP), observing a state s_t, selecting an action a_t according to a policy $\pi(a_t|s_t)$, and receiving a scalar reward r_t. The objective is to learn a policy that maximizes the expected cumulative discounted return $E_\pi[\sum_t \gamma^t r_t]$, where $\gamma \in [0,1]$ is the discount factor determining how future rewards are weighted relative to immediate ones (Sutton and Barto, 2018). Classical RL struggles when the state or action space is high-dimensional or continuous, as in offshore wind maintenance, where turbine states, weather, and logistics create vast combinations. DRL overcomes this limitation by using deep networks to approximate
25 policy and value functions, enabling end-to-end learning directly from high-dimensional or partially observed inputs such as

Table 1. Nomenclature and Acronyms

Acronym	Definition
A2C	Advantage Actor-Critic
A3C	Asynchronous Advantage Actor-Critic
CNN	Convolutional Neural Network
DCMAC	Deep Centralized Multi-Agent Actor-Critic
DDPG	Deep Deterministic Policy Gradient
DDQN	Double Deep Q-Network
DQN	Deep Q-Network
DRL	Deep Reinforcement Learning
GCN	Graph Convolutional Network
IOHMM	Input-Output Hidden Markov Model
MDP	Markov Decision Process
O&M	Operations and Maintenance
PHM	Prognostics and Health Management
POMDP	Partially Observable Markov Decision Process
PPO	Proximal Policy Optimization
QMIX	Multi-Agent Value-based RL Algorithm
RL	Reinforcement Learning
RUL	Remaining Useful Life
SAC	Soft Actor-Critic
SCADA	Supervisory Control and Data Acquisition
W-QMIX	Weighted QMIX

condition monitoring or weather data. These features make DRL particularly suitable for complex, stochastic decision problems in offshore wind O&M, where the agent must learn adaptive, long-horizon maintenance policies under uncertainty.

As shown in Figure 1, there are certain strengths of DRL that are particularly suited to address Offshore Wind O&M challenges. By continuously learning from operational data, DRL models can anticipate failures, adjust scheduling dynamically, and optimize resource allocation under uncertainty. Unlike static policies, DRL-based approaches can proactively manage maintenance operations, ensuring that interventions are timed effectively to minimize downtime and operational disruptions. Furthermore, their scalability makes them suitable for complex, multi-component wind farms, where coordinated decision-making across turbines, crews, and assets is essential.

This review is designed to provide a focused and critical examination of the application of DRL to maintenance planning in offshore wind farms. Rather than attempting an exhaustive survey of all works in the DRL domain, we have deliberately narrowed our focus to a select group of key studies that exemplify the state-of-the-art in this area. The studies were chosen primarily for their direct relevance to the unique challenges of offshore wind operations, as they address specific aspects such as harsh environmental conditions, complex logistics, and the high-dimensional nature of maintenance decision-making.

In selecting the literature, particular emphasis was placed on those contributions that not only employ DRL algorithms, but also integrate domain-specific knowledge related to offshore wind, or that can be directly translated to it. This includes, for instance, the incorporation of wind farm aerodynamics to account for wake effects, weather and sea state constraints, as well as
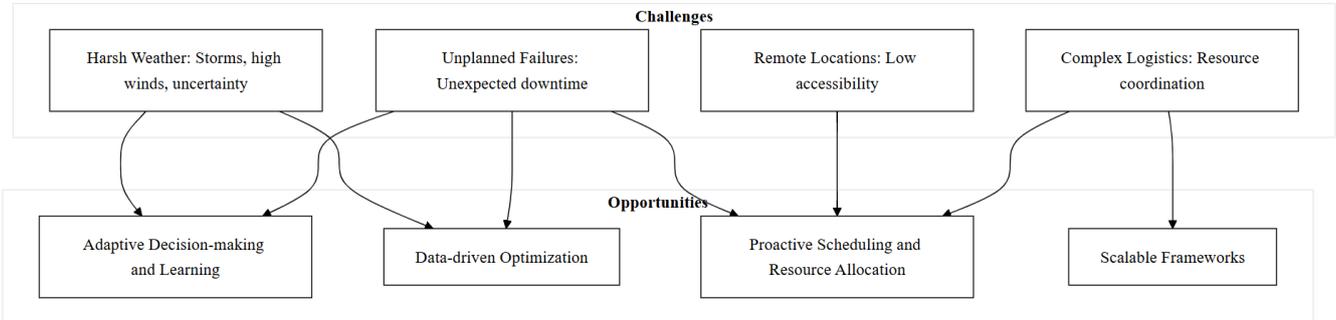
Figure 1. Challenges of offshore wind maintenance and opportunities of DRL methods

data derived from Prognostics and Health Management (PHM) systems. Moreover, the review prioritizes studies that provide performance evaluations, comparing the DRL-based strategies against traditional maintenance approaches.

The primary goal of this manuscript is to synthesize the advancements demonstrated by these representative models, criti-
45   cally assessing their strengths and identifying the limitations that still exist.

By doing so, we aim to demonstrate how DRL can effectively address the challenges of offshore wind maintenance planning, while also pinpointing areas that require further refinement. This targeted review not only clarifies the current state of research in this field but also offers insights into future research directions, particularly in the development of decision frameworks that move beyond simplistic binary repair actions.

50   The remainder of this paper is organized as follows. In Section 2, we review single-agent DRL approaches for offshore wind maintenance, highlighting key algorithms and their performance in discrete decision-making settings. Section 3 extends the discussion to multi-agent DRL frameworks, which address scalability by distributing decisions across multiple agents. In Section 4, we detail the formulations used to represent the maintenance problem, including Markov Decision Processes (MDP), Partially Observable MDP (POMDP), hierarchical and graph-based methods. In Section 5 we offer a recap of the reviewed
55   models and schematize their key features in a summary table. Section 6 summarizes the key contributions and performance improvements achieved by the reviewed DRL models. Section 7 discusses the integration of domain-specific knowledge such as wind farm aerodynamics, weather constraints, logistics, and PHM data. In Section 8, we compare simulation-based studies with real-world applications. In Section 9 we focused on what we believe is the main gap in current DRL models for maintenance planning, i.e. their reliance on a binary maintain-or-not decision. Instead, we argue that incorporating multiple levels of repair
60   actions is necessary to reflect real-world maintenance scenarios more accurately. Finally, Section 10 concludes with insights and directions for future research.

2   Single-Agent DRL Approaches for Offshore Wind O&M

Most DRL-based maintenance planners for offshore wind adopt a *single-agent* paradigm, where one agent learns an optimal policy for the entire system (e.g., a wind farm or a single turbine). This structure is suitable when a central decision-maker can coordinate all maintenance actions and information is aggregated at the farm or turbine level.

In DRL, two key functions define the learning objective: the *state–action value function* $Q(s,a)$, which estimates the expected cumulative reward of taking action a in state s, and the *state value function* $V(s)$, which measures the expected reward of being in state s and following the current policy. Different algorithm families approximate and use these functions in distinct ways, thus, among single-agent methods, three main families of DRL algorithms are most frequently applied: (i) *value-based*: value-based methods such as the Deep Q-Network (DQN) algorithm (Mnih et al., 2015), learn an approximation of $Q(s,a)$ using a deep neural network and select actions that maximize this value. Stability is achieved through experience replay and a target network. DQN and its variants (Double DQN, Dueling DQN) are effective for discrete maintenance decisions such as *"maintain"* versus *"not maintain"*.; (ii) *policy-gradient*: instead of estimating value functions, policy-gradient methods learn a parameterized policy $\pi_\theta(a|s)$ by adjusting the parameters θ in the direction of the performance gradient. Proximal Policy Optimization (PPO) (Schulman et al., 2017a) is a widely used variant that constrains policy updates within a clipped trust region, improving stability and sample efficiency for large or continuous decision spaces, such as allocating multiple maintenance crews. (iii) *actor–critic*: hybrid algorithms such as the actor-critic methods, combine both paradigms by maintaining a policy (the *actor*) and a value estimator (the *critic*). Deep Deterministic Policy Gradient (DDPG) (Lillicrap et al., 2016) and Soft Actor–Critic (SAC) (Haarnoja et al., 2018b) extend DRL to continuous control using deterministic or stochastic policies with off-policy learning, while Asynchronous Advantage Actor–Critic (A3C) (Mnih et al., 2016) accelerates training through parallel environment instances.

The flowchart in Figure 2 illustrates these single-agent DRL approaches: all methods share common initial steps (environment setup, state observation) before diverging by learning logic: DQN (green) selects actions via ϵ-greedy exploration based on Q-values; policy-gradient methods (purple) sample actions from a learned distribution and update directly via performance gradients; actor–critic methods (orange) use a critic network to evaluate actions and guide policy improvement.

The following subsections review how each family has been applied to specific O&M formulations and performance objectives.

2.1   Deep Q-Networks (DQN)

Value-based methods like DQN are popular for discrete maintenance decisions (e.g. whether to service a component now or later). For instance, Lee et al. (2025) developed a domain-informed DQN ensemble to schedule offshore wind farm maintenance tasks. They formulated maintenance scheduling as a MDP and incorporated wind wake effect models and weather variability into the state. By using convolutional layers to process spatial-temporal features (like turbine wake interactions), their DQN agent improved power generation by 11.1% compared to a baseline schedule.
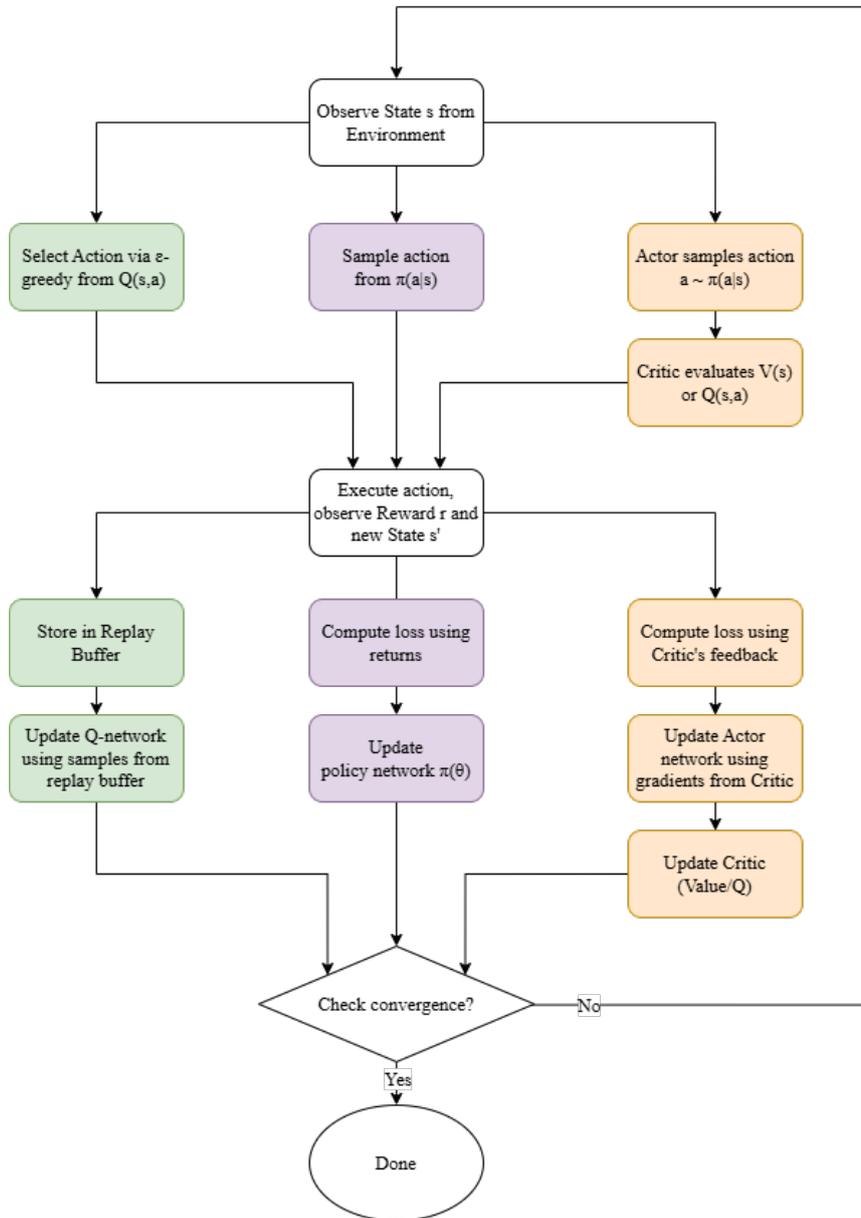
Figure 2. Overview of single-agent DRL algorithm families

Similarly, Kerkkamp et al. (2022) combined DQN with Graph Neural Networks to take into account asset topology. In
95   their framework, a single agent uses a Graph Convolutional Network (GCN) to group maintenance actions on geographically
proximate pipes, yielding more efficient schedules. The DQN+GCN approach produced more reliable networks and higher
maintenance grouping compared to a plain DQN and to conventional preventive/corrective policies.

These studies chose DQN for its stability in discrete action spaces and supplemented it with domain-informed neural architectures such as Convolutional Neural Networks (CNNs), or Graph Neural Networks (GCNs) to accelerate learning and capture dependencies. Another value-based approach is the Double DQN (DDQN) or Dueling DQN to handle large state spaces more stably, Zhang and Si (2020) tested DDQN for large state spaces in multi-component maintenance and showed better performance than simple threshold policies.

However, value-based methods can struggle when the action space or planning horizon grows large, or when the state is partially observed (e.g. uncertain component health) (Hausknecht and Stone, 2015). These challenges have led researchers to explore policy-gradient methods as well.

2.2 Policy Gradient Methods

Policy-based DRL algorithms have been applied especially where the action space is large or continuous (e.g. scheduling multiple maintenance crews). Proximal Policy Optimization (PPO) in particular is favored for its stable and sample-efficient learning (Schulman et al., 2017b), and it has been used in several maintenance studies.

Pinciroli et al. (2021) developed a PPO-based agent to optimize maintenance dispatch for a wind farm with multiple crews. They formulated the problem as a sequential decision process and included prognostic information in the state (predicted RULs of turbines from PHM systems, and even forecasted power production for upcoming days). The PPO agent learned a policy that outperformed corrective, scheduled, and threshold-based predictive maintenance benchmarks in profit maximization. Notably, the DRL policy automatically scheduled maintenance during low-power periods and anticipated failures using RUL predictions, something a simple RUL-threshold policy could not do. PPO effectively handles continuous decision-making under uncertainty and yields better long-horizon rewards than static policies.

In another example, Cheng et al. (2023b), applied both DQN and PPO to learn cost-optimal condition-based maintenance for an offshore turbine component. They investigated policies with dynamic inspection intervals and adaptive repair thresholds, formulating the decision as an MDP and comparing DRL algorithms. Both a DQN agent and a PPO agent were able to discover optimal policies under varying conditions, outperforming fixed-interval or fixed-threshold strategies by reducing lifecycle costs although, in their case, PPO performed better than DQN.

2.3 Actor–Critic and Others (DDPG, SAC, A3C)

In problems with continuous action decisions (e.g. scheduling exact timing), actor-critic methods like deep deterministic policy gradient (DDPG) (Lillicrap et al., 2015) and Soft Actor-Critic (SAC) become relevant. Zhao and Zhou (2022), for example, used a SAC algorithm to solve a wind farm maintenance scheduling problem formulated as an MDP. SAC's ability to handle continuous actions, maximizing the trade-off between reward and entropy, makes it suitable for maintenance problems requiring fine timing control. Their implementation allowed the agent to decide whether to perform maintenance on a turbine in each time period, aiming to minimize long-term cost. The SAC-based scheduler showed improved adaptability to random wind and failure events, outperforming greedy or periodic policies in simulation. Asynchronous Advantage Actor-Critic (A3C) and related algorithms have also been mentioned in the context of maintenance optimization to benefit of parallel training. While we

are not aware of specific applications of A3C to offshore wind maintenance, the algorithm's ability to run multiple environment instances in parallel can accelerate training for complex simulations. For instance, in a broader manufacturing maintenance context, A3C has been used to optimize resource allocation problems where quick convergence was needed (Mnih et al., 2016). In principle, A3C/A2C could be applied to wind farm O&M planning to speed up learning across many simulated weather

135   scenarios or failure realizations. However, stability can be an issue, so recent works have gravitated more to PPO for O&M problems.

In summary, value-based methods (DQN variants) have shown success for discrete decision-making, while policy gradient and actor-critic methods (PPO, SAC) are increasingly used for their stability in more complex or continuous action scenarios. Each algorithm is typically chosen to match the problem characteristics: e.g. DQN when the action is a discrete choice of

140   maintenance action, PPO/A3C when a rich policy representation is needed for large state spaces or partial observability, and SAC/DDPG when action decisions might be continuous or to efficiently reuse past experiences,even those generated under different policies, to improve sample efficiency and accelerate learning (Haarnoja et al., 2018a).

The discussion on single-agent DRL approaches has highlighted how tailored algorithms can effectively optimize maintenance decisions. However, as wind farms scale up and the complexity of interdependent maintenance decisions increases, a

145   shift toward distributed decision-making might become necessary. The following section explores multi-agent DRL frameworks, which distribute the decision-making process across multiple agents, thereby addressing scalability challenges while enabling coordinated maintenance planning.

3   Multi-Agent DRL in Maintenance Planning

As our environment grows in size, a multi-agent DRL (MADRL) approach can be considered to distribute the decision-making

150   across multiple agents (Lowe et al., 2017) (e.g. one agent per turbine or per subsystem).

Figure 3 contrasts the single-agent and multi-agent DRL approaches. In the single-agent framework (3a, left), one centralized policy observes the environment and makes all maintenance decisions, whereas in the multi-agent framework (3b, right), each agent receives local observations and collectively coordinates actions.

Multi-agent frameworks address the curse of dimensionality that a single agent faces when managing many components

155   simultaneously (Ogunfowora and Najjaran, 2023). In a cooperative MADRL setting, agents must learn policies that jointly optimize the overall maintenance outcome. A common approach is centralized training with decentralized execution: during learning the agents share information, but in execution each acts independently (Rashid et al., 2018).

One relevant study is Nguyen et al. (2022) (expanded in Do et al. (2024)), who optimized maintenance for a 13-component system using a Weighted QMIX algorithm. Here, each component is controlled by an agent, and a mixing network combines

160   their action-values into a global Q-value to enforce cooperation.

The "weighted" QMIX (W-QMIX) variant addresses limitations of standard QMIX by improving credit assignment to each agent's actions (Liang et al., 2025). By customizing QMIX, they overcame the exponential growth of joint action-space and achieved cost-effective policies that significantly reduced total maintenance cost compared to independent or rule-based
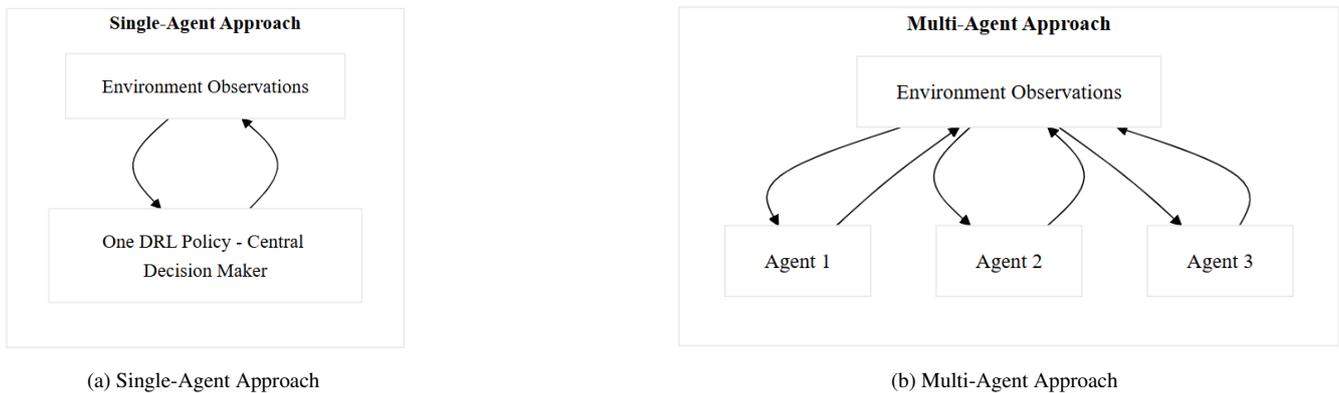
(a) Single-Agent Approach

(b) Multi-Agent Approach

Figure 3. Comparison of Single-Agent and Multi-Agent DRL Approaches

policies. In fact, their multi-agent policy outperformed a traditional threshold-based maintenance strategy, yielding 20% lower
165   cost in the case study. The agents learned to coordinate, essentially performing opportunistic maintenance on other components
when one component required service, something that is hard-coded in opportunistic heuristics but emerged naturally via learn-
ing. Notably, they simplified the architecture by using a branching neural network (one network outputting multi-component
actions).

Figure 4 presents a high-level overview of how local Q-values from multiple agents are combined into a single joint Q-value
170   through a central mixing network. At the top, global state observations and individual agents' local Q-values feed into the
network. Within the mixing network, these local estimates are merged. The output at the bottom is a single joint Q-value,
enabling decentralized agents to learn coordinated policies that account for global objectives.

Another multi-agent perspective is taken by Andriotis and Papakonstantinou (2019), who developed a Deep Centralized
Multi-Agent Actor-Critic (DCMAC) algorithm (Andriotis and Papakonstantinou, 2021). This algorithm treats each component
175   as an "actor" with individual actions, and uses a centralized critic to evaluate the joint outcome. Their method allowed individu-
alized component-level decisions (like a multi-agent system) but maintained a single value function for the overall system. This
hybrid approach achieved strong results on high-dimensional maintenance problems, outperforming time-based and condition-
based benchmarks. DCMAC can be seen as bridging single and multi-agent methods: it's centrally trained on the whole state,
but action vectors are factorized per component. The success of DCMAC and similar centralized-training approaches again
180   underlines that decomposing the action space among multiple decision-makers is a powerful strategy for scalability.

While most offshore wind DRL studies to date use a single centralized agent, the multi-agent perspective is highly relevant.
A wind farm can be seen as a team of turbines (or a team of maintenance crews) that could each be an agent. Multi-agent DRL
can explicitly model interactions like shared resources (e.g. a vessel cannot fix two turbines at once) and learn decentralized
policies. For example, one could have a DRL agent for each maintenance vessel coordinating via a mixing network to maximize
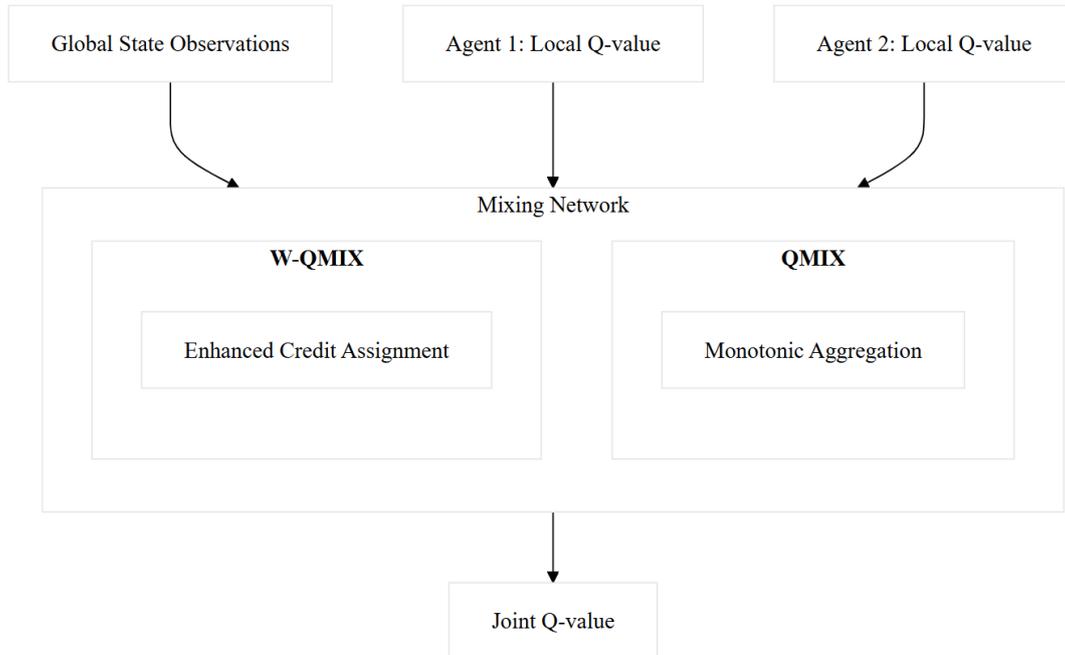185   farm availability.

Figure 4. Multi-agent mixing network architecture

Nevertheless, multi-agent approaches introduce challenges such as non-stationarity during training and coordination complexity. To avoid these issues, for example, Pinciroli et al. (2021) effectively used a single PPO agent to dispatch multiple crews, which could be interpreted as a centralized multi-action policy rather than fully decentralized agents.

An interesting future direction is to combine multi-agent RL with the physical layout of a wind farm, e.g. treating turbines
190   as agents that learn when to request maintenance, or crews as agents learning which turbine to service, to further scale O&M optimization. In summary, multi-agent DRL is a promising direction that can address scalability and modularity in offshore wind maintenance, ensuring that solutions remain effective as the number of assets grows.

Having examined both single-agent and multi-agent DRL frameworks for maintenance planning, it is clear that the choice of algorithm is intricately linked to how the underlying problem is modeled. The next section focuses on the core methodologies
195   and decision frameworks used, ranging from Markov Decision Processes (MDP) to Partially Observable MDPs (POMDPs), hierarchical and graph-based representations, that provide the foundation for these DRL approaches. This discussion will clarify how the characteristics of the problem formulation drive the design and performance of the DRL models.

4 Problem Formulation

Formulating the maintenance planning problem correctly is a core requirement for DRL. In literature, we see formulations as Markov Decision Processes (MDPs), Partially Observable MDPs (POMDPs), and even graph-based representations, each chosen to capture the nature of the decision environment.

4.1 Markov Decision Process (MDP)

Many works assume the system state is fully observable. For example, if one uses direct sensor readings or known component health states as the state, the decision process can be modeled as an MDP.

Cheng et al. (2023a) formulate the CBM decision as an MDP where the state might include the current damage level or time since last inspection. They defined actions such as whether to inspect or repair, with rewards based on cost.

Similarly, the DQN-based scheduling by Lee et al. (2025) uses an MDP where the state includes turbine power outputs (affected by wake and weather) and maintenance statuses, assuming those are known to the agent.

The reward design typically combines negative maintenance costs and downtime losses into a single scalar reward (or profit) to guide the agent toward cost-optimal decisions, as in Pinciroli et al. (2021).

MDP formulations are simpler and allow use of standard DRL algorithms, but they rely on having a reliable estimator of the system's health state.

4.2 Partially Observable MDP (POMDP)

In reality, a turbine's true health or failure time distribution is uncertain, the agent only has observations (e.g. aggregated condition monitoring signals or RUL predictions). To account for this, some studies use POMDP formulations. In a POMDP, the agent maintains a belief to make decisions under uncertainty.

Kerkkamp et al. (2022) also formulate maintenance planning as a POMDP on a graph, where the underlying deterioration states are partially observed through inspections.

Similarly, Lee and Mitici (2023) treat their predictive maintenance problem for aircraft components as a POMDP, using a CNN to process raw sensor data into an observation for the DRL agent.

The choice of POMDP acknowledges that maintenance decisions must be made with imperfect information, and DRL agents in this setting are trained to be more robust to uncertainty (e.g. scheduling maintenance a bit earlier to hedge against uncertain failure times). Methodologically, solving a POMDP with DRL often means using belief state features or statistical features of uncertainty (such as predicted failure probability) in the state.

4.3 Graph and Network-Based Representations

Some complex systems benefit from graph-based formulations. Kerkkamp et al. (2022) is an example where the asset network structure (a sewer network in their case) is encoded as a graph, and a GCN is used to inform the DRL agent.

While their domain was not wind, one can imagine an offshore wind farm graph where nodes are turbine components and edges could represent spatial proximity or electrical/functional dependencies. This approach could let the agent learn policies that consider component interactions (e.g. if neighboring turbines' maintenance can be combined). In their framework, the graph-based state and GCN embedding encouraged the agent to group maintenance geographically, improving efficiency.

4.4 Hierarchical and interpretable models

To tackle the black-box nature of DRL, Abbas et al. (2024) introduced a hierarchical DRL framework for turbofan engine maintenance that combines an Input-Output Hidden Markov Model (IOHMM) with a DQN-like agent. The high-level IOHMM module interprets sensor data to detect the likely fault mode or degradation state (providing a human-understandable diagnostic), while the low-level DRL module learns the optimal replacement or repair policy given that inferred state. This two-level approach achieved performance on par with end-to-end DRL, but with the added benefit that decisions could be traced to identifiable health-state estimates.

In safety-critical domains like aerospace or offshore energy, such interpretability is valuable for gaining trust in the AI's recommendations. Moreover, by narrowing the policy search to focus on critical decisions (informed by the HMM), the agent avoids spurious actions in sparse failure domains.

Although turbofan engines differ from wind turbines, the concept is relevant: they use a probabilistic model to identify health states and provide an interpretable layer, and the DRL agent makes maintenance decisions at a higher level. This yields a more transparent policy, which could be valuable in offshore wind where operators demand understanding of the AI's decisions (Adadi and Berrada, 2018). Such hierarchical or hybrid frameworks (combining physics-based or expert models with learning) are a way to inject domain knowledge directly into the DRL algorithm, improving learning speed and trustworthiness.

Figure 5 illustrates different frameworks commonly used to represent state information in Deep Reinforcement Learning (DRL) models for maintenance decision-making. Starting from an initial state S, the flowchart shows four distinct ways the state can be represented or processed before making a decision. The MDP formulation (blue) assumes full access to the true system state. The POMDP approach (yellow) highlights the partial observability of real-world systems requiring the agent to infer underlying states from limited observations $O(S)$ of the true state. The Graph-based method (green) structures state information using nodes and edges relationships to capture spatial or topological dependencies, allowing the agent to consider how interconnected assets affect one another's maintenance needs. Finally, the Hierarchical approach (red) incorporates domain-specific insights, either from expert knowledge or physics-based models. After selecting an action A based on the chosen representation, the system receives a reward R and transitions to a new state S', looping back to begin a new decision-making cycle.

4.5 Decision Frameworks and Objectives

Across these formulations, the decision-making frameworks can vary in objective. Some agents aim to minimize total cost (including repair costs, downtime costs, and possibly penalty for using resources) (Kerkkamp et al., 2022). Others aim to maximize availability or energy production (profit) (Lee et al., 2025; Pinciroli et al., 2021).
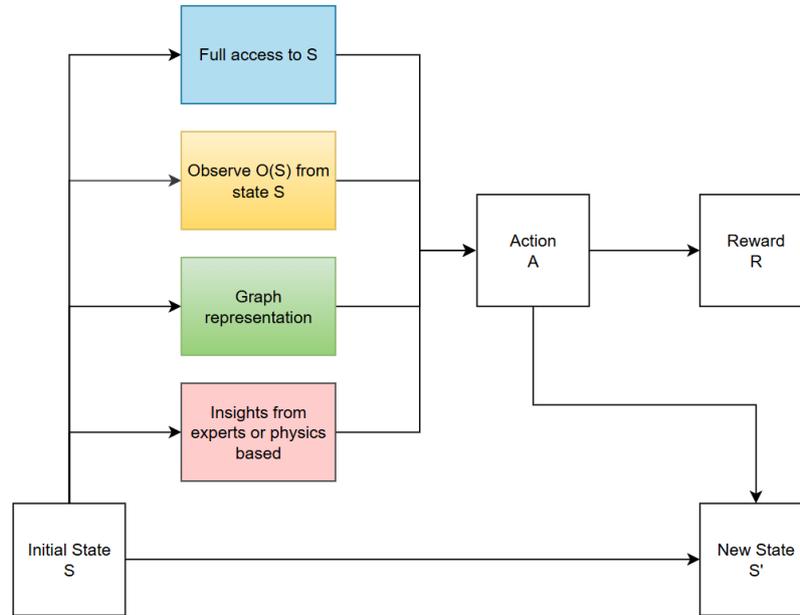
Figure 5. Overview of problem formulations in DRL models: MDP (blue), PO-MDP (yellow), graph/network-based (green), and hierarchical (pink) approaches

These are effectively two sides of the same coin, since maximizing uptime or output will implicitly minimize downtime losses. The reward function should, in fact, include terms for lost revenue when a turbine is down, crew/vessel dispatch costs, spare part costs, and maybe even penalties for equipment degradation.

For example, Pinciroli et al. (2021) designed a reward equal to the short-term profit (energy revenue minus O&M costs) at
265 each decision step, so the PPO agent's cumulative reward corresponds to total profit. Cheng et al. (2023b) focused on cost rates, giving negative rewards for inspection or repair costs and for failures, to encourage the agent to find the policy with minimum average cost.

In multi-agent settings, a global reward is often used for full cooperation (as in QMIX, where agents maximize a shared cost-saving metric).

270 Some works also impose constraint handling in the formulation. For instance, maintenance actions might be invalid under certain weather conditions; a realistic environment simulator will simply not allow those actions (or will assign a large negative reward if attempted). Thus, ensuring decisions are feasible (e.g. not sending a crew when waves are too high) can be done by action masking or via constraint-penalty in the reward. Recent research even explores incorporating optimization constraints into neural network design (e.g. using attention masks to enforce constraints) as in (Kazemian et al., 2024), though this is still
275 emerging in O&M applications.

In summary, the methodologies range from straightforward MDP models with fully observable states to sophisticated POMDP and graph-based models that embrace the complexities of offshore wind maintenance. The trend is toward more

realistic problem formulations, acknowledging partial observability, incorporating spatial and logistical structure, and aligning the reward with business metrics (cost or profit). The following section provides a structured summary of these methodologies, highlighting key aspects such as agent design, algorithm choices, and problem formulations in a comparative table. This summary aims to offer a clear and concise reference for understanding the variations in DRL-based maintenance planning approaches and their defining characteristics.

5 Comparative Summary of DRL Approaches for Offshore Wind O&M

The table below compares the DRL-based maintenance planning approaches reviewed, highlighting their key features such as agents, algorithms and problem formulations. All the mentioned approaches aim to optimize maintenance scheduling but differ in the algorithms and formulations used. The column *agent* refers to whether one policy controls the whole system or multiple coordinating policies exist, *algorithm* shows which training method was used, and *problem formulation* indicates how the maintenance decision problem is modeled for the agent.

Table 2. Comparison of DRL Approaches for Offshore Wind Farm Maintenance

Reference	Agent		Algorithm						Problem Formulation			
	Single Agent	Multi Agent	DQN	PPO	SAC	QMIX	W-QMIX	DCMAC	MDP	PO-MDP	Graph-based	Hierarchical
Lee et al. (2025)	✓		✓						✓			
Abbas et al. (2024)	✓		✓									✓
Do et al. (2024)		✓				✓	✓		✓			
Lee and Mitici (2023)	✓									✓		
Cheng et al. (2023b)	✓		✓	✓					✓			
Zhao and Zhou (2022)	✓				✓				✓			
Kerkkamp et al. (2022)	✓		✓							✓	✓	
Nguyen et al. (2022)		✓				✓	✓		✓			
Pinciroli et al. (2021)	✓			✓					✓			
Chatterjee and Dethlefs (2021)	✓		✓						✓			
Andriotis and Papakonstantinou (2021)		✓						✓	✓			

In Figure 6, we provide a comparative view of the distribution of key features across the reviewed literature. 6a shows the proportion of single- versus multi-agent frameworks. 6b outlines the distribution of algorithms such as DQN, PPO, SAC, and QMIX variants, showing that DQN remains the most commonly used DRL algorithm despite the explosion of the action space, which grows with the number of components or maintenance tasks, limiting its applicability in larger-scale problems. Finally, 6c highlights the prevalence of MDP and PO-MDP-based modeling.

With a clear understanding of the diverse methodologies used to model offshore wind maintenance planning, we now turn to the practical impact of these approaches. The following section summarizes the key contributions and performance improve-

(a) Single vs. Multi-Agent Distribution   (b) Algorithms Distribution   (c) Problem Formulations Distribution
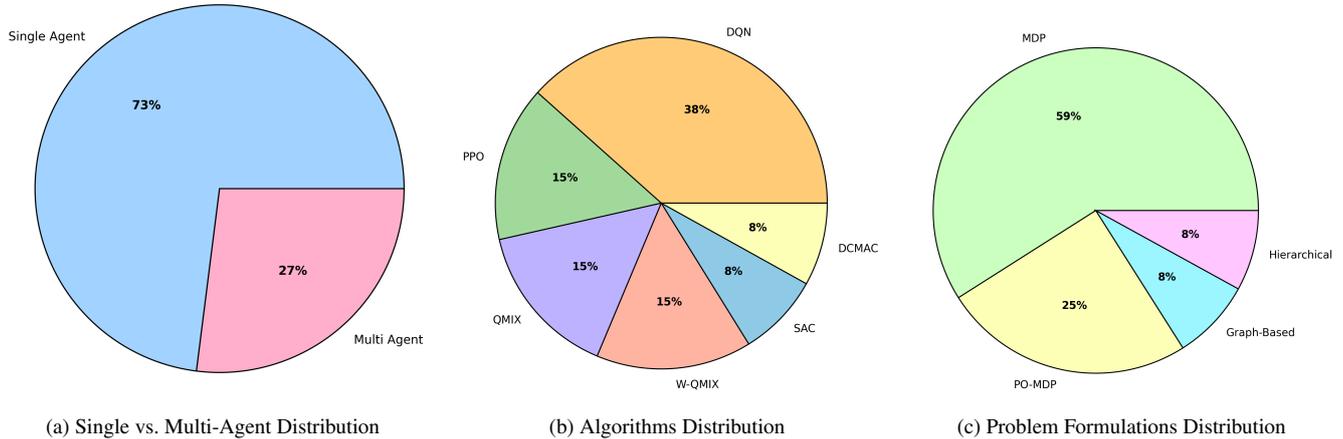
Figure 6. Comparative view of single vs. multi-agent methods, main DRL algorithms, and problem formulations in the reviewed literature.

ments achieved through the application of DRL, illustrating how these methodological choices translate into tangible benefits such as cost reduction, improved reliability, and enhanced operational efficiency.

6 Key Benefits of DRL Models

The application of DRL to offshore wind O&M has yielded notable improvements over traditional maintenance strategies,
300   as documented in the reviewed studies. The application of DRL to offshore wind O&M has shown clear advantages over conventional maintenance strategies, achieving lower costs, higher availability, and more adaptive planning. The reviewed studies highlight five recurring benefits: (i) *cost and downtime reduction*, as agents learn to time interventions "just in time" before failure; (ii) *enhanced predictive maintenance*, through integration of Remaining Useful Life (RUL) data and operational context; (iii) *opportunistic maintenance*, by grouping actions and exploiting favorable conditions; (iv) *improved reliability and*
305   *safety*, via proactive scheduling and embedded risk constraints; and (v) *computational scalability*, enabling optimization of large, stochastic systems.

The following subsections discuss each benefit in detail, illustrating how DRL contributes to more cost-efficient and resilient offshore wind maintenance planning.

6.1 Cost and Downtime Reduction

310   A primary goal is lowering maintenance costs and turbine downtime compared to baseline strategies (reactive or scheduled). DRL agents have demonstrated the ability to significantly reduce unplanned failures and associated costs.

For example, Cheng et al. (2023b) reported that their learned policy with adaptive inspection/repair timing led to a noticeable reduction in lifecycle cost relative to fixed-interval maintenance.

In Lee and Mitici (2023), the DRL-based policy reduced unplanned downtime and maintenance cost in a multi-component system by 95.6% versus conventional periodic maintenance.

These improvements come from the agent's ability to optimize the timing of maintenance: servicing components "just in time" before failure, but not too early to waste life. DRL policies effectively find this sweet spot by continuous learning and adjustment.

6.2 Predictive (PHM-based) Strategies

Many wind operators use condition-based triggers (like RUL thresholds from prognostics) to plan maintenance. DRL can enhance these predictive strategies by adding dynamic decision-making. As noted in Pinciroli et al. (2021), the DRL policy outperformed a pure RUL-threshold policy by considering not only the component health but also external factors such as power demand and crew availability. In other words, whereas a standard predictive maintenance strategy says "replace component X when its $RUL < Y\,days$," a DRL agent might learn "replace component X when $RUL < Y\,days$ *and* a maintenance team is idle *and* a low wind period is coming up," thereby minimizing impact. This kind of contextual decision-making led to higher reward (profit) in their experiments. We see a similar theme in Lee et al. (2025): their DQN agent, augmented with wake effect knowledge, boosted energy production beyond what a wake-unaware strategy achieved. By learning the true optimal policy through trial and error, DRL approaches can exceed the performance of both corrective maintenance (which incurs high downtime) and simple predictive rules (which might be myopic or inflexible).

6.3 Opportunistic Maintenance

DRL has shown strength in exploiting opportunistic maintenance opportunities that humans or simple policies might miss. For instance, in multi-component scenarios, an agent can coordinate maintenance on multiple turbines in one go to avoid repeated downtime. Do et al. (2024) demonstrated this with their multi-agent approach where the learned policy effectively grouped maintenance tasks to save on shared downtime costs, beating a policy that treats components independently. Even in single-agent setups, agents learn to use times of low production or existing outages to perform additional repairs. The PPO agent in Pinciroli's work learned to wait for low wind output days to schedule maintenance, which is an opportunistic behavior yielding higher rewards. Huang et al. (2020) observed that, even when not explicitly programmed, DRL agents naturally learn to group multiple repairs together, thereby reducing repetitive downtime and sharing high logistics costs over several interventions, similar findings can be found in Dong et al. (2021) and Valet et al. (2022). In the context of offshore wind, for example, an agent might schedule a minor repair on one turbine when a vessel is already en route for a major repair on a neighboring turbine, effectively reducing additional transit costs.

6.4 Reliability and Safety

An important point is that DRL policies can improve reliability metrics (e.g. mean time between failures, availability) by preventing failures proactively. Lee and Mitici (2023) noted fewer failures in their DRL-maintained system than a conventional

345 approach. Additionally, DRL can incorporate safety constraints (like not allowing maintenance deferral beyond a limit) via rewards or state features. The hierarchical approach by Abbas (2024) is aimed at safety-critical maintenance, by integrating an interpretable model, they ensure the DRL decisions for turbofan engines remain within safe bounds and can be understood by engineers. In offshore wind, ensuring that a DRL policy does not inadvertently run turbines to catastrophic failures is very important. Studies so far show that with proper reward design (heavily penalizing failures), the agents naturally learn to avoid
350 risky deferrals.

6.5 Computational Feasibility

Another finding across the literature is that DRL can handle high-dimensional problems that were previously intractable by brute force optimization. Maintenance scheduling for a wind farm with many turbines, each with several components, is a huge combinatorial problem over a long horizon. Model-based or brute-force methods struggle to consider all contingencies
355 and long-term effects (Chen et al., 2024). DRL, with its experience-driven learning, provides feasible solutions. Nevertheless, training can be computationally intensive (e.g. WQMIX took 12 hours in the 13-component case (Nguyen et al., 2022)), although once trained, the policy can execute decisions in real-time. Some studies also accelerate learning by transfer or imitation. For example, Pinciroli et al. (2021) initialized their PPO agent via imitation learning from a heuristic policy to shorten training time. This hybrid approach marries human insight with AI optimization. The result is a practical decision-
360 support tool that can quickly recommend which turbine to maintain and when, given the current observations.

The consensus of recent work is that DRL-based maintenance planning consistently outperforms static strategies in simulation, often by a wide margin in cost savings or uptime. These improvements stem from DRL's ability to learn optimal scheduling under uncertainty, adapt to varying conditions (weather, load demands), and coordinate multiple decisions in a way that human-designed rules cannot easily mimic.

365 While the performance gains of DRL-based maintenance strategies are evident, their success is further amplified by the integration of domain-specific knowledge. The next section focuses on how incorporating elements such as wind farm aerodynamics, weather constraints, logistical considerations, and PHM data not only enriches the state representations but also guides the learning process toward more realistic and reliable maintenance policies.

7 Incorporating Offshore Wind-Specific Knowledge in DRL Models

370 A fundamental aspect of training and deploying DRL agents for maintenance planning is the integration of domain-specific knowledge. The following subsections explore how different forms of domain knowledge can enhance decision-making: (i) *wind farm aerodynamic* interactions that affect energy yield; (ii)*weather and sea state* constraints that determine accessibility; (iii) *logistics* and crew-related considerations; (iv) *prognostic and health management data* for predictive maintenance; (v) *economic factors* such as market prices and budget limits, and finally, (vi) the inclusion of *multi-level repairs* that reflect real
375 operational practices.

7.1 Wind Farm Aerodynamics

In a wind farm, turbines cast aerodynamic wakes that reduce the output of downwind turbines (Vermeer et al., 2003). In Lee et al. (2025), the authors considered this by making their DRL agent wake-aware. They fed a wake interaction model into the state, and used an ensemble of DQN models to capture different wake scenarios. By incorporating multiple wake models, their

380 agent learned maintenance decisions that minimize farm power loss due to wakes, leading to higher overall energy production.

This domain knowledge is particularly important for tightly spaced wind farms where wake losses are significant; a purely self-learned agent without wake inputs might need enormous training experience to "discover" such effects, whereas providing a wake model upfront accelerates learning.

The result is a policy that schedules maintenance such that either the waking effect is minimal (e.g. performing maintenance

385 when winds are low or from directions that don't affect other turbines) or that multiple affected turbines are maintained together to collapse the wake loss into a single period.

7.2 Weather and Sea State

Offshore maintenance is heavily weather-dependent, high waves, strong winds, or storms can prevent crew transfers and repairs (Jenkins et al., 2021). Some DRL studies explicitly include weather in the environment.

390 Chatterjee and Dethlefs (2021) demonstrated a DRL approach for planning vessel transfers to turbines, integrating real SCADA data and weather conditions. Their agent could prioritize critical repairs and navigate the stochastic availability of weather windows, something traditional scheduling struggles with (Borsotti et al., 2024). By training on historical weather patterns, the DRL policy learns, for example, to take advantage of a calm sea state to perform a repair even if it's slightly early, because waiting might mean a long weather delay.

395 Similarly, Pinciroli's state included predicted power (which indirectly reflects wind forecast) to help the agent plan around periods of low wind (often correlated with calmer weather) (Pinciroli et al., 2021; Ogunfowora and Najjaran, 2023).

In practice, one can input wave height forecasts or wind speed forecasts into the DRL state; the agent will then learn not to "choose" an action that requires travel during bad weather. Domain knowledge here ensures feasibility and robustness: the agent that knows about weather will inherently develop a maintenance schedule that aligns with seasonal weather patterns,

400 reducing cancellations and idle times.

7.3 Logistics

Offshore O&M involves vessels, helicopters, crews, and spare parts, logistical aspects that greatly affect cost. DRL models have started to include these. In the multi-crew PPO model by Pinciroli et al. (2021), the state and action were designed to capture crew positions and availability. The environment simulation accounted for travel times to turbines and repair durations.

405 This domain realism meant the learned policy actually coordinates crew movements: e.g. sending Crew A to a turbine that will finish repair soon, while Crew B waits at the depot until a large failure occurs. By encoding travel time and multiple crews, the DRL agent learned to avoid wasted trips and to keep crews utilized, emulating optimal routing and scheduling decisions.

In Kerkkamp et al. (2022), logistics is addressed in a spatial sense by using a GCN to group geographically close maintenance. In an offshore wind context, that could translate to handling nearby turbines in one outing to minimize transit.

410   Even without an explicit graph, a DRL agent can learn from cost feedback that doing maintenance on neighboring turbines back-to-back saves the transit cost of multiple separate trips. Future research is incorporating more detailed logistics, such as vessel capacity, fuel cost, and inventory of spare parts, into the DRL state/reward. The benefit of doing so is that the learned policy becomes a holistic O&M schedule that respects not just failure risks but also supply chain and labour constraints.

7.4   Prognostics and Health Management (PHM) Data

415   Almost all DRL approaches in this area use PHM outputs (like condition monitoring and RUL predictions), which is essential domain knowledge for predictive maintenance. The difference is in how they incorporate it. For instance, Abbas et al. (2024) and Abbas (2024) integrate an Input-Output Hidden Markov Model to classify health states of turbofan engines and feed this into the DRL agent.

In offshore wind, one could use a discretized health state (e.g. "good", "degraded", "critical") as part of the state space,
420   which is easier for an agent to handle than raw sensor readings. Lee and Mitici (2023) approach of using a CNN on sensor data before the DRL agent is another way, essentially letting a deep learning model extract relevant features (vibration patterns, etc.) which portray the health knowledge.

By combining PHM and DRL, these frameworks close the loop from condition monitoring to decision-making. The advantage is clear: the better the agent's awareness of actual component condition (even if inferred), the better it can time main-
425   tenance. PHM can also be embed in the model by shaping the reward as well, e.g. a large penalty for a failure is effectively encoding the idea "a catastrophic gearbox failure is very bad" which the agent must learn.

PHM-driven rewards can also be used, such as giving a small penalty for running a component in a highly degraded state (reflecting higher wear or risk).

7.5   Economic Factors

430   Domain knowledge also includes economic factors like energy price and maintenance cost structure. Some works incorporate dynamic electricity prices or contractual penalties into the reward. For instance, if energy price forecasts are available, a DRL agent could decide to do maintenance when energy price (hence lost revenue) is low.

While not explicitly seen in the reviewed models, Attention-based approaches are starting to include market price as part of the input to O&M scheduling models (Kazemian et al., 2024).
435   In offshore wind, including such factors could align maintenance not just with technical needs but also with business cycles (e.g. perform maintenance during low demand seasons or when subsidy/price is low). Another economic constraint is the budget or resource limit, DRL can consider these by capping certain rewards or through state variables (like remaining budget).
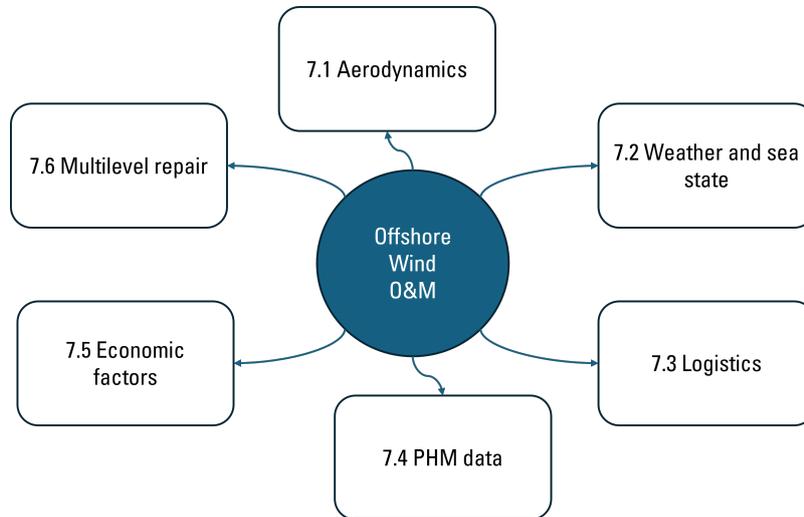
Figure 7. Domain-specific knowledge for offshore wind

7.6 Multi-Level Repairs

Traditional maintenance models in offshore wind operations typically reduce decisions to a simple binary choice, either repair or not. However, real-world observations show that turbine downtime arises from a spectrum of failures. For instance, industry data reveals that roughly 70% of downtime is caused by major repairs, about 17% by minor repairs, with the remainder due to simple resets (Carroll et al., 2017).

This suggests that maintenance actions in the field are inherently multi-level, ranging from minor fixes that temporarily restore performance to major overhauls or full component replacements.

While incorporating these multi-level actions enriches the state-action representation, it also exposes a significant gap in current DRL models for offshore wind O&M. Most existing studies focus on binary decision frameworks.

The lack of integration of multi-level maintenance actions is discussed in greater detail in Section 9, where we explore the implications of this refined modeling on cost, reliability, and overall operational efficiency.

By integrating these domain specifics, summarized in Figure 7, DRL models become more realistic and effective. Pure model-free DRL is powerful, but in a complex domain like offshore wind, guiding the learning with known physics (wake loss), operational constraints (weather, logistics), and expert knowledge (PHM interpretations) greatly improves performance.

All the studies reviewed have, in one way or another, blended domain knowledge into their DRL approach: Lee et al. added wake/convective layers, Chatterjee added weather data, Kerkkamp added graph relations, Pinciroli added RUL and power forecasting, Abbas added HMM interpretable layers, etc. This synergy of domain expertise and reinforcement learning is key to developing trustworthy, high-performance maintenance policies that industry can adopt.

Integrating domain-specific insights has shown clear potential to enhance DRL performance in simulated settings. However, translating these promising simulation results into real-world applications presents additional challenges. The following section

compares simulation-based studies with emerging real-world implementations, discussing how high-fidelity simulations and digital twins are paving the way for practical deployment in offshore wind maintenance operations.

460 ## 8 Simulation-Based Studies vs. Real-World Applications

Simulation-based research has been the predominant way to develop and evaluate DRL for wind farm maintenance. All the studies reviewed above rely on simulated environments, typically a stochastic model of turbine degradation and failure, combined with models of maintenance actions (costs, durations, effects) and often weather or logistics simulators.

For instance, Lee et al. (2025) used a simulation of wind dynamics and turbine wakes to train their DQN ensemble; Pinciroli
465 et al. (2021) built a custom simulator for turbine failures and crew assignments to test PPO. Simulation is essential because it provides a safe and flexible sandbox to train DRL agents (which often require millions of decision steps for convergence). Researchers can speed up or repeat scenarios (like many years of operation) to expose the agent to rare events, something impossible to do quickly in the real world.

Key insights from simulation studies include the significant performance gains of DRL policies over traditional maintenance
470 strategies. Many papers report that their learned policies yield lower cost or higher availability than periodic (time-based) or reactive (run-to-failure) maintenance. For example, Pinciroli et al.'s agent outperformed corrective and age-based schedules with fewer failures and lower cost, mirroring Andriotis and Papakonstantinou (2021)'s results against periodic policies. Such results, consistently observed in simulation, build a compelling case for applying DRL in practice.

That said, real-world applications of DRL in offshore wind O&M are still in early stages, but are beginning to emerge.
475 A notable example is the work by Lee et al. (2025) which was conducted in partnership with an industry research institute (KEPCO in Korea). Their DQN-based maintenance scheduling approach was developed with a view toward large-scale wind farms (100+ turbines) and addressed practical issues like wake losses and weather downtime.

While the deployment of a trained agent in a live wind farm has not been reported yet, the involvement of an industrial stakeholder and the real-world fidelity of the simulation (including measured wake effects) indicate a step toward actual adoption.

480 In fields like aviation and manufacturing, some DRL-based maintenance planners have been tested on real data if not deployed directly. For instance, the turbofan case by Abbas et al. (2024) used NASA engine datasets to train and validate their approach. This kind of validation on real-world data builds confidence that the policies will translate from simulation to reality. Moreover, ongoing advances in digital twins for wind farms (Zhang et al., 2024) (high-fidelity replicas of turbines and operations) may enable DRL agents to be trained or at least fine-tuned in an environment that closely mimics reality.

485 The next section explores this gap by examining how DRL-based planning models can incorporate multi-level maintenance strategies, allowing agents to choose among different maintenance tasks.

9 Multi-Level Maintenance Strategies in DRL Planning Models

Traditional maintenance models in offshore wind often reduce decisions to a binary choice (e.g., to repair or not). In a DRL formulation, the maintenance planning problem can be recast as a Markov decision process where the state includes asset features such as component condition, age and weather windows, while the action space is expanded beyond a simple "maintain or not" decision.

Instead, enabling the agent to choose among multiple repair options. Such an approach would allow the agent to balance cost and reliability by, for example, deploying a less expensive interim repair when system health is marginally degraded or committing to a full repair only when necessary.

Incorporating minor repairs as a viable action can prevent small degradations from escalating into catastrophic failures. DRL agents trained on multilevel maintenance tasks can learn to execute low-level fixes when early signs of degradation appear, thereby extending component life and improving overall system reliability. Wei et al. (2019), for example, demonstrated that a DRL-based policy for structural maintenance maintained high reliability by optimally balancing minor and major interventions across numerous components.

Potential avenues for enabling a DRL agent to consider multi-action maintenance planning include:

- **Expanded Action Spaces:** Researchers have begun explicitly modeling a range of actions, such as "do nothing," "perform minor repair," "conduct major repair," or "replace component." For example, Zhang et al. (2023) formulate an infinite-horizon DRL maintenance problem where a component's health can be partially recovered through an imperfect repair or fully restored via corrective maintenance. This expanded action space helps the agent learn which level of intervention yields the optimal long-term cost and reliability trade-off.

- **Parameterized and Hybrid Actions:** To manage the complexity arising from multiple discrete repair choices combined with continuous variables (e.g., the timing of intervention), advanced approaches employ parameterized action spaces. In one instance, a parameterized PPO algorithm was developed to handle mixed discrete-continuous decisions, effectively allowing the agent to adjust both the type of repair and the timing simultaneously (Zhang et al., 2023). This structured action space helps maintain convergence stability while exploring complex repair policies.

- **Multi-Agent Decomposition:** Another promising strategy is to decompose the large-scale maintenance problem by modeling each turbine or even each component as an individual RL agent within a cooperative framework. For example, Su et al. (2022) address the explosion of the action space in multilevel preventive maintenance by treating each machine as an independent agent that coordinates with others. Such a decomposition not only alleviates scalability issues but also enables the agents to learn localized strategies that can later be integrated for holistic wind farm maintenance.

Despite the promise of these approaches, challenges remain in training and deployment. The high dimensionality of both state and action spaces, especially in a wind farm with hundreds of turbines, can lead to a combinatorial explosion in decision possibilities. Techniques such as multi-agent reinforcement learning are being explored to address these scalability concerns.

Cross-industry insights from manufacturing, aerospace and civil infrastructure further suggest that lessons learned in one domain (e.g., mission-aware planning or adaptive grouping strategies) can be effectively translated to offshore wind maintenance planning.

In summary, by moving beyond binary choices, these models could capture the inherent complexity of real-world O&M practices and facilitate the development of policies that more accurately balance short-term fixes with long-term reliability. This advancement would represent a significant step toward more realistic and effective DRL-based maintenance planning in offshore wind operations.

The concluding section synthesizes the insights gathered from the reviewed models, underscoring the strengths, current limitations, and future directions for integrating DRL into operational decision-making frameworks that could revolutionize maintenance planning in the renewable energy sector.

10 Conclusion

The literature demonstrates that DRL is a promising approach for offshore wind farm maintenance planning. By learning from interactions in a simulated environment, DRL agents can devise maintenance policies that outperform traditional corrective, time-based, and other predictive strategies on key metrics like cost, downtime, and energy production. Both single-agent and multi-agent frameworks have been explored: single-agent DRL has succeeded in optimizing complex maintenance schedules by considering long-term consequences, while multi-agent DRL offers a path to scaling these solutions to larger systems by decentralizing decisions. Moreover, the most successful studies embed domain-specific knowledge, from wake physics to weather patterns to prognostic models, into the DRL process, creating hybrid solutions that learn efficiently and behave realistically.

The reviewed works highlight several advantages of DRL in offshore wind O&M: adaptive scheduling that responds to the actual condition of turbines, opportunistic maintenance that smartly times actions to minimize impact on operations, and the ability to handle the high dimensionality of scheduling problems that defy mathematical or brute-force optimization. For example, DRL agents have learned to schedule maintenance during low wind periods (Ogunfowora and Najjaran, 2023), to cluster repairs and save vessel trips (Kerkkamp et al., 2022), and to prevent failures by reacting to prognostic alarms better than fixed rules. These capabilities translate into quantifiable gains: double-digit percentage improvements in cost savings or energy output in case studies are common (Lee et al., 2025; Nguyen et al., 2022).

However, challenges remain before DRL is commonplace in live offshore wind operations. Safety and trust are critical aspects, operators need assurance that an AI agent won't recommend catastrophic decisions. This is why interpretability (as in the hierarchical HMM approach) and extensive testing are crucial. Computational efficiency is also a concern: multi-agent or long-horizon DRL can be computationally intensive in the training phase, though improvements in algorithms and hardware mitigate this. Additionally, integration with existing maintenance management systems requires user-friendly interfaces and perhaps human-in-the-loop designs (where human planners can review or override AI suggestions).

Moreover, a critical limitation in current DRL applications is the overly simplistic treatment of repair actions. Most methods consider only one kind of repair, typically reducing the decision to whether to replace a component. In practice, maintenance is a multifaceted process that often involves choosing among various repair strategies, each with distinct implications for system performance and cost. For instance, an optimal policy should not only determine the optimal timing of an intervention but also decide which specific repair tasks to undertake based on the current condition of components. Addressing this gap requires developing agents capable of discerning a richer set of actions that reflect the complexities of real-world maintenance tasks.

For practitioners and researchers, these findings support moving toward DRL-based decision support tools for wind farm O&M. As offshore wind farms continue to grow and data from operations accumulate, DRL approaches aim to become integral in optimizing maintenance planning, ultimately lowering the cost of renewable energy and improving the reliability of wind power generation.

References

Abbas, A.: A Hierarchical Framework for Interpretable, Safe, and Specialised Deep Reinforcement Learning, Doctoral thesis, Technological University Dublin, https://arrow.tudublin.ie/ittthedoc/17, 2024.

570 Abbas, A. N., Chasparis, G. C., and Kelleher, J. D.: Hierarchical framework for interpretable and specialized deep reinforcement learning-based predictive maintenance, Data & Knowledge Engineering, 149, 102 240, https://doi.org/10.1016/j.datak.2023.102240, 2024.

Adadi, A. and Berrada, M.: Peeking Inside the Black-Box: A Survey on Explainable Artificial Intelligence (XAI), IEEE Access, PP, 1–1, https://doi.org/10.1109/ACCESS.2018.2870052, 2018.

Andriotis, C. P. and Papakonstantinou, K. G.: Deep reinforcement learning driven inspection and maintenance planning under incomplete
575 information and constraints, Reliability Engineering & System Safety, 212, 107 551, https://doi.org/10.1016/j.ress.2021.107551, 2021.

Borsotti, M., Negenborn, R., and Jiang, X.: Model predictive control framework for optimizing offshore wind O&M, in: Advances in Maritime Technology and Engineering, pp. 533–546, CRC Press, https://doi.org/https://doi.org/10.1201/9781003508762-65, 2024.

Carroll, J., McDonald, A., Dinwoodie, I., McMillan, D., Revie, M., and Lazakis, I.: Availability, operation and maintenance costs of offshore wind turbines with different drive train configurations, WIND ENERGY, 20, 361–378, https://doi.org/10.1002/we.2011, 2017.

580 Chatterjee, J. and Dethlefs, N.: Scientometric review of artificial intelligence for operations & maintenance of wind turbines: The past, present and future, Renewable and Sustainable Energy Reviews, 144, 111 051, https://doi.org/https://doi.org/10.1016/j.rser.2021.111051, 2021.

Chen, M., Kang, Y., Li, K., Li, P., and Zhao, Y.-B.: Deep reinforcement learning for maintenance optimization of multi-component production systems considering quality and production plan, Quality Engineering, 0, 1–12, https://doi.org/10.1080/08982112.2024.2373362, 2024.

585 Cheng, J., Liu, Y., Li, W., and Li, T.: Deep reinforcement learning for cost-optimal condition-based maintenance policy of offshore wind turbine components, Ocean Engineering, 283, 115 062, https://doi.org/10.1016/j.oceaneng.2023.115062, 2023a.

Cheng, J., Liu, Y., Li, W., and Li, T.: Deep reinforcement learning for cost-optimal condition-based maintenance policy of offshore wind turbine components, Ocean Engineering, 283, 115 062, https://doi.org/https://doi.org/10.1016/j.oceaneng.2023.115062, 2023b.

Do, P., Nguyen, V.-T., Voisin, A., Iung, B., and Neto, W. A. F.: Multi-agent deep reinforcement learning-based maintenance optimization for
590 multi-dependent component systems, Expert Systems with Applications, 245, 123 144, https://doi.org/10.1016/j.eswa.2024.123144, 2024.

Dong, W., Zhao, T., and Wu, Y.: Deep Reinforcement Learning Based Preventive Maintenance for Wind Turbines, in: 2021 IEEE 5th Conference on Energy Internet and Energy System Integration (EI2), pp. 2860–2865, https://doi.org/10.1109/EI252483.2021.9713457, 2021.

Fox, H., Pillai, A. C., Friedrich, D., Collu, M., Dawood, T., and Johanning, L.: A Review of Predictive and Prescriptive Offshore Wind Farm
595 Operation and Maintenance, ENERGIES, 15, https://doi.org/10.3390/en15020504, 2022.

Haarnoja, T., Zhou, A., Abbeel, P., and Levine, S.: Soft Actor-Critic: Off-Policy Maximum Entropy Deep Reinforcement Learning with a Stochastic Actor, CoRR, abs/1801.01290, http://arxiv.org/abs/1801.01290, 2018a.

Haarnoja, T., Zhou, A., Abbeel, P., and Levine, S.: Soft Actor-Critic: Off-Policy Maximum Entropy Deep Reinforcement Learning with a Stochastic Actor, arXiv preprint arXiv:1801.01290, https://arxiv.org/abs/1801.01290, 2018b.

600 Hausknecht, M. J. and Stone, P.: Deep Recurrent Q-Learning for Partially Observable MDPs, CoRR, abs/1507.06527, http://arxiv.org/abs/1507.06527, 2015.

Huang, J., Chang, Q., and Arinez, J.: Deep reinforcement learning based preventive maintenance policy for serial production lines, Expert Systems with Applications, 160, 113 701, https://doi.org/https://doi.org/10.1016/j.eswa.2020.113701, 2020.

Jenkins, B., Prothero, A., Collu, M., Carroll, J., McMillan, D., and McDonald, A.: Limiting Wave Conditions for the Safe Maintenance of
605   Floating Wind Turbines, in: EERA DEEPWIND'2021, edited by Tande, J., Kvamsdal, T., and Muskulus, M., vol. 2018 of *Journal of
       Physics Conference Series*, NTNU; European Energy Res Alliance; Res Council Norway, ISSN 1742-6588, https://doi.org/10.1088/1742-
       6596/2018/1/012023, european-Energy-Research-Alliance (EERA) 18th Deep Sea Offshore Wind R and D Digital Conference (EERA
       DeepWind), SINTEF, ELECTR NETWORK, JAN 13-15, 2021, 2021.

Kazemian, I., Yildirim, M., and Ramanan, P.: Attention is All You Need to Optimize Wind Farm Operations and Maintenance, https://arxiv.
610   org/abs/2410.24052, 2024.

Kerkkamp, D., Bukhsh, Z., Zhang, Y., and Jansen, N.: Grouping of Maintenance Actions with Deep Reinforcement Learning and Graph
       Convolutional Networks, in: Proceeding of the 14th International Conference on Agents and Artificial Intelligence, vol. 2, pp. 574–585,
       SciTePress Digital Library, https://doi.org/10.5220/0000155600003116, 14th International Conference on Agents and Artificial Intelli-
       gence, ICAART 2022, ICAART 2022 ; Conference date: 03-02-2022 Through 05-02-2022, 2022.

615 Lee, J. and Mitici, M.: Deep reinforcement learning for predictive aircraft maintenance using probabilistic Remaining-Useful-Life prognos-
       tics, Reliability Engineering & System Safety, 230, 108 908, https://doi.org/https://doi.org/10.1016/j.ress.2022.108908, 2023.

Lee, N., Woo, J., and Kim, S.: A deep reinforcement learning ensemble for maintenance scheduling in offshore wind farms, Applied Energy,
       377, https://doi.org/https://doi.org/10.1016/j.apenergy.2024.124431, 2025.

Liang, J., Miao, H., Li, K., Tan, J., Wang, X., Luo, R., and Jiang, Y.: A Review of Multi-Agent Reinforcement Learning Algorithms,
620   Electronics, 14, https://doi.org/10.3390/electronics14040820, 2025.

Lillicrap, T., Hunt, J., Pritzel, A., Heess, N., Erez, T., Tassa, Y., Silver, D., and Wierstra, D.: Continuous control with deep reinforcement
       learning, CoRR, 2015.

Lillicrap, T. P., Hunt, J. J., Pritzel, A., Heess, N., Erez, T., Tassa, Y., Silver, D., and Wierstra, D.: Continuous Control with Deep Reinforcement
       Learning, in: International Conference on Learning Representations (ICLR), https://arxiv.org/abs/1509.02971, arXiv:1509.02971, 2016.

625 Lowe, R., WU, Y., Tamar, A., Harb, J., Pieter Abbeel, O., and Mordatch, I.: Multi-Agent Actor-Critic for Mixed Cooperative-Competitive
       Environments, in: Advances in Neural Information Processing Systems, edited by Guyon, I., Luxburg, U. V., Bengio, S., Wallach, H.,
       Fergus, R., Vishwanathan, S., and Garnett, R., vol. 30, Curran Associates, Inc., https://proceedings.neurips.cc/paper_files/paper/2017/file/
       68a9750337a418a86fe06c1991a1d64c-Paper.pdf, 2017.

Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A. A., Veness, J., Bellemare, M. G., Graves, A., Riedmiller, M., Fidjeland, A. K., Ostrovski, G.,
630   Petersen, S., Beattie, C., Sadik, A., Antonoglou, I., King, H., Kumaran, D., Wierstra, D., Legg, S., and Hassabis, D.: Human-level control
       through deep reinforcement learning, Nature, 518, 529–533, https://doi.org/10.1038/nature14236, 2015.

Mnih, V., Badia, A., Mirza, M., Graves, A., Lillicrap, T., Harley, T., Silver, D., and Kavukcuoglu, K.: Asynchronous Methods for Deep
       Reinforcement Learning, Proceedings of Machine Learning Research, https://doi.org/10.48550/arXiv.1602.01783, 2016.

National Renewable Energy Laboratory: Offshore Wind Energy Market Assessment 2022, National Renewable Energy Laboratory, https:
635   //www.nrel.gov/wind/offshore-market-assessment.html, 2022.

Nguyen, V.-T., Do, P., Voisin, A., and Iung, B.: Weighted-QMIX-based Optimization for Maintenance Decision-making of
       Multi-component Systems, in: Proceedings of the European Conference of the PHM Society 2022, vol. 7, pp. 360–367,
       https://doi.org/10.36001/phme.2022.v7i1.3319, 2022.

Ogunfowora, O. and Najjaran, H.: Reinforcement and deep reinforcement learning-based solutions for machine
640   maintenance planning, scheduling policies, and optimization, Journal of Manufacturing Systems, 70, 244–263,
       https://doi.org/https://doi.org/10.1016/j.jmsy.2023.07.014, 2023.

Pinciroli, L., Baraldi, P., Ballabio, G., Compare, M., and Zio, E.: Deep Reinforcement Learning Based on Proximal Policy Optimization for the Maintenance of a Wind Farm with Multiple Crews, Energies, 14, https://doi.org/10.3390/en14206743, 2021.

Rashid, T., Samvelyan, M., de Witt, C. S., Farquhar, G., Foerster, J. N., and Whiteson, S.: QMIX: Monotonic Value Function Factorisation
645   for Deep Multi-Agent Reinforcement Learning, CoRR, abs/1803.11485, http://arxiv.org/abs/1803.11485, 2018.

Schulman, J., Wolski, F., Dhariwal, P., Radford, A., and Klimov, O.: Proximal Policy Optimization Algorithms, arXiv preprint arXiv:1707.06347, https://arxiv.org/abs/1707.06347, 2017a.

Schulman, J., Wolski, F., Dhariwal, P., Radford, A., and Klimov, O.: Proximal Policy Optimization Algorithms, CoRR, abs/1707.06347, http://arxiv.org/abs/1707.06347, 2017b.

650   Su, J., Huang, J., Adams, S., Chang, Q., and Beling, P. A.: Deep multi-agent reinforcement learning for multi-level preventive maintenance in manufacturing systems, Expert Systems with Applications, 192, 116 323, https://doi.org/https://doi.org/10.1016/j.eswa.2021.116323, 2022.

Sutton, R. S. and Barto, A. G.: Reinforcement Learning: An Introduction, MIT Press, Cambridge, MA, 2 edn., http://incompleteideas.net/book/the-book-2nd.html, 2018.

655   Valet, A., Altenmüller, T., Waschneck, B., May, M. C., Kuhnle, A., and Lanza, G.: Opportunistic maintenance scheduling with deep reinforcement learning, Journal of Manufacturing Systems, 64, 518–534, https://doi.org/10.1016/j.jmsy.2022.07.016, 2022.

Vermeer, N.-J., Sørensen, J., and Crespo, A.: Wind turbine wake aerodynamics, Progress in Aerospace Sciences - PROG AEROSP SCI, 39, 467–510, https://doi.org/10.1016/S0376-0421(03)00078-2, 2003.

Wei, S., Jin, X., Bao, Y., and Li, H.: Reinforcement Learning in Maintenance of Civil Infrastructures, in: Proceedings of the 36th International
660   Conference on Machine Learning (ICML 2019), Workshop on Reinforcement Learning for Real Life (RL4RealLife), https://openreview.net/pdf?id=Hkl8c3e6cV, 2019.

Zhang, C., Li, Y.-F., and Coit, D. W.: Deep Reinforcement Learning for Dynamic Opportunistic Maintenance of Multi-Component Systems With Load Sharing, IEEE Transactions on Reliability, 72, 863–877, https://doi.org/10.1109/TR.2022.3197322, 2023.

Zhang, E., Shen, F., Liu, S., Chen, G., Zhang, F., and Li, S.: Offshore wind power digital twin modeling system for intelligent operation and
665   maintenance applications, E3S Web of Conferences, 546, https://doi.org/10.1051/e3sconf/202454602010, 2024.

Zhang, N. and Si, W.: Deep reinforcement learning for condition-based maintenance planning of multi-component systems under dependent competing risks, Reliability Engineering & System Safety, 203, 107 094, https://doi.org/https://doi.org/10.1016/j.ress.2020.107094, 2020.

Zhao, F. J. and Zhou, Y.: Wind Farm Maintenance Scheduling Using Soft Actor-Critic Deep Reinforcement Learning, in: 2022 Global Reliability and Prognostics and Health Management (PHM-Yantai), pp. 1–6, https://doi.org/10.1109/PHM-Yantai55411.2022.9942116,
670   2022.