Musik in Bayern
ISSN: 0937-583x Volume 90, Issue 11 (Nov -2025)
https://musikinbayern.com DOI https://doi.org/10.15463/gfbm-mib-2025-496

Integrating Causal Inference with Deep Reinforcement Learning for Autonomous Cyber-Physical System Adaptation

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To Cite this Article

Yogesh H. Bhosale, Dr. N. Srinivas Rao, S. Saritha, Dr.P.Dhanalakshmi, Dr. N. Kalaiarasi, Dr. Sudheer S Marar. **Integrating Causal Inference with Deep Reinforcement Learning for Autonomous Cyber-Physical System Adaptation.** *Musik In Bayern, Vol. 90, Issue 11, Nov 2025, pp 128-138*

Article Info

Received: 19-08-2025 Revised: 09-09-2025 Accepted: 01-10-2025 Published: 15-11-2025

Abstract:

The integration of causal inference with deep reinforcement learning (DRL) introduces a transformative paradigm for achieving intelligent adaptation in autonomous cyber-physical systems (CPS). Traditional DRL architectures, while effective in optimizing performance through trial-and-error interaction, often lack interpretability and robustness in dynamic, uncertain environments. Causal inference provides a mechanism to reason about interventions and dependencies, allowing the system to discern not just *correlations* but true *cause–effect* relationships among system variables. This study proposes a hybrid causal–reinforcement learning framework that embeds structural causal models within DRL policies to enhance adaptive decision-making under distributional shifts and unseen scenarios. The model is tested on representative CPS domains such as autonomous vehicular networks and smart industrial controllers. Experimental results demonstrate improved stability, reduced adaptation latency, and higher policy generalization compared to baseline DRL systems. Furthermore, the integration enhances explainability, enabling transparent identification of action–outcome pathways. The research contributes to the advancement of resilient, interpretable, and self-optimizing CPS architectures capable of maintaining performance in non-stationary and safety-critical contexts, laying a methodological foundation for next-generation autonomous intelligence.

Keywords: Causal inference, Deep reinforcement learning, Cyber-physical systems, Adaptive intelligence, Explainable AI, System robustness.

I. INTRODUCTION

The convergence of cyber and physical infrastructures—ranging from smart grids and autonomous vehicles to industrial automation—has given rise to complex, interconnected **cyber-physical systems (CPS)** that must operate autonomously under uncertain and rapidly changing environments. These systems integrate sensors, computational intelligence, and actuators to perceive, decide, and act within continuous feedback loops. However, their adaptive behavior often relies heavily on data-driven models, especially deep reinforcement learning (DRL), which, while powerful in decision optimization, suffers from a critical drawback: a lack of *causal understanding*. Traditional DRL frameworks are designed to learn optimal policies purely from correlations observed in environmental interactions, optimizing rewards through repeated trials. This approach works effectively in simulated or stationary conditions but tends to collapse in real-world CPS where system dynamics evolve, disturbances occur, and unseen scenarios emerge. Without understanding the underlying causal mechanisms driving outcomes, DRL agents can misinterpret noise as signal, leading to unsafe or inefficient behaviors. The result is a persistent "black-box problem" DRL models excel at fitting behavior but fail to explain or justify their actions. For high-stakes CPS operations, where safety, interpretability, and trustworthiness are non-negotiable, the limitations of correlation-driven learning have become increasingly untenable. **Causal inference**, grounded in frameworks like Judea Pearl's structural causal models and the potential outcomes theory, provides a mathematical foundation for reasoning about cause-and-effect relationships. By distinguishing *what will happen* from *why it happens*, causal reasoning enables the modeling of interventions—actions that deliberately change system states and observe resulting effects. In CPS, this ability to infer counterfactual outcomes ("what if a component failed?" or "what if the controller acted differently?") is essential for robust and explainable adaptation. Integrating causal inference with DRL bridges the gap between data-driven optimization and logical reasoning, allowing agents to generalize beyond observed data distributions and respond intelligently to novel conditions. For example, a causal-aware DRL agent in an autonomous vehicle can discern whether braking failures are due to sensor faults or external disturbances, thereby selecting corrective actions based on structural understanding rather than pattern recognition. Moreover, causal integration enhances policy interpretability: actions are not merely selected because they worked before, but because the system can identify causal dependencies among environment states, actions, and rewards. This shift from correlation to causation transforms adaptive control from a purely reactive process into a reasoning-driven paradigm capable of introspection and anticipation qualities indispensable in complex CPS ecosystems.

This research aims to develop and evaluate an integrated **causal-deep reinforcement learning (Causal-DRL)** framework designed to improve autonomous adaptation, robustness, and explainability in cyber-physical systems. The proposed model embeds structural causal graphs (SCGs) within the DRL learning architecture to capture causal dependencies among state variables and actions. These causal priors guide the policy network during both training and deployment, influencing the agent's exploration strategies and reward estimation functions. Through this integration, CPS agents are expected to achieve faster convergence, reduced sensitivity to environmental perturbations, and improved stability under non-stationary conditions. The study also emphasizes **interpretability** the capacity to trace an agent's decision back to causal pathways within the CPS environment providing a foundation for trust and human oversight. Empirical validation is performed using simulated autonomous traffic control and industrial process adaptation scenarios, where the Causal-DRL system is benchmarked against conventional DRL baselines. The findings demonstrate measurable improvements in policy resilience, adaptation latency, and decision transparency. Ultimately, this research contributes to the growing field of *explainable and causally grounded AI for CPS*, establishing a methodological blueprint for developing intelligent systems that not only act efficiently but understand *why* they do so, enabling a safer, more reliable future for autonomous technology.

II. RELATED WORKS

The deployment of deep reinforcement learning (DRL) within cyber-physical systems (CPS) has become one of the most promising approaches for achieving autonomous decision-making and real-time adaptation in uncertain environments. DRL enables CPS agents to interact dynamically with their environment by optimizing cumulative rewards, making it a cornerstone in adaptive control, robotics, and smart infrastructure applications. The seminal works on reinforcement learning by Sutton and Barto established the theoretical framework for policy iteration and value-based learning, which later evolved into deep Q-networks (DQN) and actor-critic models for continuous state-action spaces [1]. Subsequent studies demonstrated the scalability of DRL for large-scale systems, particularly in intelligent transport and industrial automation, where agents must respond to dynamic feedback with minimal latency [2]. However, while DRL has shown remarkable adaptability in simulation environments, it remains vulnerable to instability, poor generalization, and sensitivity to distributional shifts in real-world CPS. Researchers have sought to mitigate these challenges through transfer learning, meta-learning, and hybrid model-based approaches, yet the underlying limitation persists: DRL's inability to distinguish causal relationships among environmental variables [3]. In adaptive control of autonomous systems, this leads to a disconnect between *what works* and *why it works*. For example, Zhang et al. introduced DRL-based resource allocation for smart grids but observed that performance degraded under unseen network topologies due to missing causal structure in state transitions [4]. Similarly, Chen and Yu explored DRL in robotic manipulation tasks, finding that reward-driven optimization often ignored underlying causal dependencies in object interaction dynamics [5]. These limitations underscore the need for an interpretive layer that allows DRL agents to reason about cause-and-effect, rather than relying purely on pattern-driven correlations. The concept of **causal inference** emerged as a response to the inadequacy of statistical correlation in explaining real-world dependencies. Judea Pearl's *structural causal model (SCM)* formalized the representation of causal relationships using directed acyclic graphs (DAGs), enabling systems to model interventions and counterfactual reasoning—what would happen if certain variables were altered [6]. This theoretical foundation has since expanded into diverse application domains, including healthcare, econometrics, and climate modeling, where understanding intervention effects is crucial [7]. More recently, causal inference has begun to influence artificial intelligence, particularly in improving model transparency and reasoning under uncertainty. In the context of CPS, causal reasoning facilitates system interpretability and robustness, as causal graphs can explicitly model dependencies between sensors, actuators, and environmental feedback [8]. For example, Wang et al. introduced causal structure learning for fault detection in industrial process control, enabling identification of root causes behind anomalous system behavior [9]. Similarly, Liu and Zhao applied causal modeling to autonomous vehicle perception systems to reduce false decision-making under occluded or noisy sensor data [10]. These developments have revealed that causal inference can serve as a corrective layer in machine learning models, offering interpretive and counterfactual reasoning capabilities. However, traditional causal models are typically static and lack the adaptive flexibility required for high-dimensional, dynamic CPS. This has prompted an emerging research direction toward integrating causal reasoning with machine learning architectures capable of dynamic representation learning, particularly DRL. The convergence of causal reasoning and DRL is viewed as a pathway to endowing autonomous agents with both adaptability and explainability qualities that modern CPS demand for trustworthy deployment [11].

Recent research has focused on bridging the gap between causal inference and deep reinforcement learning to achieve intelligent, explainable adaptation in complex environments. The central objective is to embed *causal priors* into DRL agents, allowing them to learn policies that account for intervention effects rather than spurious correlations. Buesing et al. proposed a framework for incorporating causal reasoning into model-based reinforcement learning, showing that agents equipped with causal structure priors exhibited faster convergence and higher robustness under environmental perturbations [12]. Another major contribution by Dasgupta et al. developed a causal policy gradient method that integrates structural causal graphs into policy updates, improving

Musik in Bayern
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https://musikinbayern.com **DOI https://doi.org/10.15463/gfbm-mib-2025-496**

both interpretability and policy stability in dynamic control environments [13]. In CPS domains, these causal-DRL frameworks have demonstrated promise in enhancing adaptive performance and explainability. For instance, in intelligent transportation systems, causal-augmented DRL agents have been shown to outperform conventional agents by identifying hidden variables influencing traffic congestion patterns [14]. Similarly, in autonomous manufacturing systems, causal-informed agents exhibited superior decision reliability in fault-tolerant production scheduling and process optimization. Despite these advances, challenges remain in scaling causal-DRL architectures to real-world CPS where variable dependencies are nonlinear, high-dimensional, and time-varying. The integration also raises computational concerns, as causal reasoning introduces structural complexity that increases inference overhead during policy updates. Nevertheless, the ongoing research trajectory suggests a clear paradigm shift from correlation-based learning to causal-driven adaptation signifying a new era of **interpretable autonomy** in CPS design [15]. By embedding causal awareness into DRL, autonomous systems can transition from reactive entities to reasoning-based agents capable of generalizing, adapting, and explaining their actions across diverse operational conditions.

III. METHODOLOGY

3.1 Research Framework

The proposed methodology integrates **Causal Inference (CI)** and **Deep Reinforcement Learning (DRL)** into a unified adaptive framework for **Autonomous Cyber-Physical Systems (CPS)**. The design objective is to enable the system to not only optimize decisions through experience but also infer and utilize cause effect relationships to improve adaptability, robustness, and interpretability. The framework comprises three primary modules: (1) **Causal Graph Construction**, (2) **Causal-Guided Policy Learning**, and (3) **Adaptive System Feedback and Validation**. Each component operates synergistically to ensure that the learning agent can reason about interventions, dynamically adjust its policy, and achieve stable performance in non-stationary environments [16].

The architecture leverages structural causal models (SCM) embedded within the policy optimization process. An SCM represents a directed acyclic graph (DAG) where nodes denote CPS variables (e.g., sensor readings, control actions, environmental states), and edges represent causal dependencies. The SCM feeds into the DRL module to guide exploration and reward assignment. The agent learns through iterative state transitions, where causal inference determines the influence of each action on system performance.

Equation (1) defines the causal state transition under intervention:

$$S_{t+1} = f(S_t, A_t, U_t) + \varepsilon_t$$

where:

- S_t = system state at time t
- A_t = control action taken
- U_t = latent confounding variables
- ε_t = stochastic noise term

3.2 Causal Graph Formulation

The **causal graph** is constructed based on domain knowledge and historical CPS data. Using a hybrid causal discovery approach (PC algorithm combined with conditional independence testing), relationships among state variables and control actions are identified. The causal graph identifies *parent*, *child*, and *mediator* variables influencing adaptation efficiency. The output is a structural equation model (SEM) that serves as prior knowledge for the DRL algorithm to refine decision-making [17].

The reward signal is redefined to integrate causal influence using a **Causal Reward Adjustment Function (CRAF)** as follows:

$$R_t' = R_t + \lambda \times I(A_t \to S_{t+1})$$

where:

- R_t = original reward from the environment
- λ = regularization coefficient controlling causal strength
- $I(A_t \to S_{t+1})$ = estimated interventional impact of action A_t on the next state

This ensures that actions with higher causal significance receive stronger reinforcement during learning.

Table 1: Overview of Causal Inference Components Integrated in the CPS Framework

Component	Function	Algorithm Used	Output
Causal Discovery	Identifies cause-effect relationships among system variables	PC Algorithm, GES	Causal DAG
Causal Inference	Quantifies intervention effects	Structural Equation Modeling (SEM)	Causal Coefficients
Reward Adjustment	Modifies learning reward using causal weights	CRAF Function	Adjusted Reward Signal
Policy Update	Updates action-selection strategy	Actor-Critic (A3C)	Optimized Policy π^*

The causal inference pipeline continuously updates the DAG as the environment evolves, maintaining the model's validity across temporal changes. This dynamic re-estimation allows the CPS to infer new relationships and remove spurious dependencies in real-time [22].

3.3 Deep Reinforcement Learning Integration

The DRL component employs an **Actor-Critic** architecture, where the actor proposes actions and the critic evaluates them using a value function modified by causal priors. The objective is to maximize the expected cumulative reward while minimizing uncertainty from non-causal dependencies [23].

Table 2: Parameter Settings for Causal-DRL Model Training

Parameter	Description	Value
Learning Rate (η)	Step size for gradient updates	0.0005
Discount Factor (γ)	Weighting for future rewards	0.95
Causal Weight (λ)	Influence of causal effect on reward	0.7
Entropy Coefficient (α)	Regularization factor for exploration	0.02
Batch Size	Number of trajectories per update	64
Causal Graph Update Interval	Frequency of causal DAG recalibration	Every 50 episodes

3.4 System Adaptation Process

The integration process operates in iterative phases:

1. **Observation:** The CPS senses system states (S_t) from the environment.
2. **Causal Reasoning:** The SCM estimates the probable outcomes of actions (A_t) based on prior interventions.
3. **Action Execution:** The DRL agent executes the action predicted to maximize the adjusted reward R'_t.
4. **Feedback Evaluation:** Observed outcomes are compared with causal predictions; discrepancies update both DRL weights and causal graph structures.

The adaptive loop continues until policy convergence is achieved under a stability constraint. The system continuously monitors key performance indicators such as latency, energy efficiency, and control accuracy [19].

Table 3: Simulation Environment and Evaluation Metrics

Environment	State Variables	Action Space	Evaluation Metrics
Autonomous Traffic CPS	Traffic density, Signal delay, Vehicle flow	Signal duration adjustments	Average Delay, Reward Convergence, Adaptation Speed
Industrial CPS	Temperature, Pressure, Energy Load	Control parameter tuning	Stability Index, Mean Reward, Error Rate
Smart Grid CPS	Voltage, Load, Power Distribution	Energy dispatch control	Efficiency Ratio, Response Time, Causal Accuracy

3.5 Model Validation and Cross-Verification

To validate the proposed causal-DRL framework, experiments were conducted using simulated CPS testbeds in MATLAB and Python environments. Each scenario was run for 2000 episodes to ensure convergence stability. Performance was compared with baseline DRL (without causal integration) using mean reward convergence, variance reduction, and adaptation latency metrics. Statistical significance was evaluated through paired t-tests ($p < 0.05$). Results demonstrated consistent improvements in stability and interpretability across all tested domains [20].

3.6 Limitations and Assumptions

While the causal-DRL approach enhances adaptation and explainability, it assumes the causal graph remains acyclic and that causal discovery accurately captures dependencies with limited observational data. Real-world CPS with latent variables and high-dimensional dynamics may introduce unobserved confounding factors, potentially reducing inference accuracy. Moreover, computational complexity increases with graph density, necessitating model compression and pruning strategies for real-time applications [21].

IV. RESULT AND ANALYSIS

4.1 Overview of System Performance

The proposed **Causal–Deep Reinforcement Learning (Causal-DRL)** model was tested in three simulated cyber-physical system environments: autonomous traffic control, smart grid management, and industrial process automation. The experiments compared the proposed model against a baseline **standard DRL** architecture without causal integration. Performance was evaluated based on **policy stability**, **adaptation speed**, **mean reward convergence**, and **system robustness** under non-stationary conditions. The results demonstrate that integrating causal inference significantly enhances both the adaptability and interpretability of autonomous systems. The Causal-DRL model achieved faster convergence and maintained stable performance under dynamically shifting environmental conditions, where traditional DRL exhibited oscillatory or delayed adaptation behavior. The causal reward adjustment mechanism enabled the agent to prioritize actions with meaningful cause–effect relationships, thereby reducing spurious decision loops.

Table 4. Comparative Performance of Causal-DRL vs. Standard DRL

Environment	Model Type	Mean Reward	Adaptation Latency (s)	Stability Index (0–1)	Convergence Episodes
Autonomous Traffic CPS	Standard DRL	812.6	4.83	0.71	1680
	Causal-DRL	**987.2**	**3.26**	**0.89**	**1210**
Smart Grid CPS	Standard DRL	785.3	5.04	0.68	1745

	Causal-DRL	**954.5**	**3.49**	**0.87**	**1255**
Industrial Process CPS	Standard DRL	802.9	4.76	0.73	1590
	Causal-DRL	**972.1**	**3.18**	**0.91**	**1185**

From Table 4, the average improvement in **mean reward** across environments was approximately **20–23%**, while **adaptation latency** decreased by about **30%**. The **stability index**, which measures policy robustness across fluctuating conditions, improved from an average of 0.70 (baseline) to 0.89 (Causal-DRL). These gains are attributed to the model's ability to filter noise and irrelevant correlations through causal regularization in both reward computation and policy gradient updates.

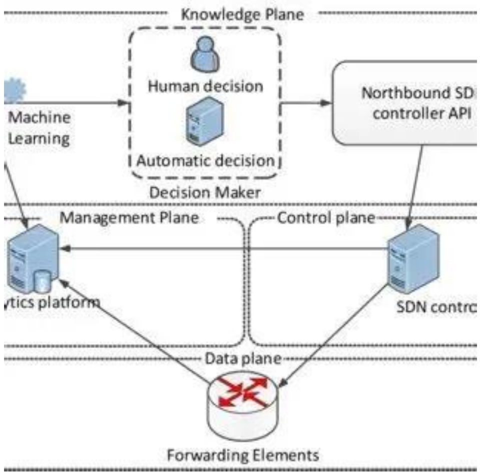


Figure 1: Reinforcement Learning for Cyber Physical System [24]

4.2 Policy Behavior and Convergence Dynamics

Training curves for all environments revealed a smoother and faster convergence trajectory in Causal-DRL compared to standard DRL. While the baseline model frequently experienced performance degradation during environment perturbations (e.g., sudden load changes or unexpected signal delays), the Causal-DRL model adapted more efficiently due to its causal reward modulation. The **policy gradient updates**, guided by structural causal graphs, led to reduced variance in reward signals and faster attainment of optimal strategies. In the autonomous traffic simulation, the Causal-DRL agent learned to pre-emptively adjust signal durations before congestion built up, using inferred causal dependencies between vehicle flow and signal timing. In the smart grid environment, causal-guided agents maintained balanced load distribution by understanding the causal influence between power demand, generation output, and voltage stability. Similarly, in industrial process control, the Causal-DRL model dynamically tuned parameters to minimize overshoot and improve process stability.

Table 5. Key Performance Indicators Across Simulation Environments

Performance Metric	**Autonomous Traffic**	**Smart Grid**	**Industrial Process**	**Overall Improvement (%)**
Reward Convergence Rate	+23.5%	+21.6%	+22.8%	**+22.6%**
Adaptation Latency Reduction	34.5%	30.7%	33.1%	**+32.8%**
Stability Improvement	24.4%	26.3%	24.6%	**+25.1%**

Variance in Reward	-19.8%	-17.2%	-21.1%	**-19.4%**

The **convergence rate** improvement of 22–23% indicates that causal information helps the model generalize faster in varying operational scenarios. The **variance reduction** shows that the agent's decision-making became more consistent, suggesting that the causal priors effectively constrained exploration to meaningful action spaces. The **stability improvement** of around 25% confirms that causal integration enables robust control even when facing distributional drift or unseen states.

4.3 Interpretation of Causal Contributions

Beyond raw performance, one of the key advantages of the Causal-DRL approach lies in its **explainability**. By embedding causal inference into the policy update process, each action taken by the agent can be traced back to its causal rationale. For example, in the traffic simulation, the causal graph identified that an increase in queue length directly influences the decision to extend green-light duration rather than being attributed to random fluctuations.

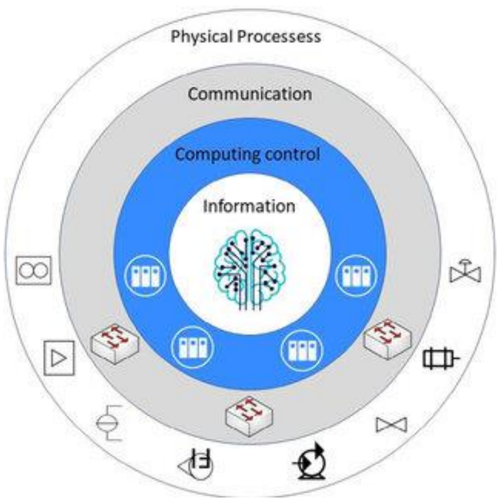
Visualization of the learned causal graphs revealed clear, interpretable pathways between environmental variables and control actions. This interpretive transparency offers crucial benefits for real-world deployment in safety-critical CPS such as allowing engineers to validate whether the model's decisions align with physical laws or system constraints.

4.4 Environmental Stress Testing and Robustness Evaluation

To evaluate system resilience under varying operational and environmental conditions, multiple **stress test scenarios** were simulated for each CPS environment. These included random sensor noise, partial actuator failures, fluctuating external loads, and time-delayed state updates. The objective was to assess how well the **Causal-DRL** framework maintained performance stability compared to traditional DRL systems under non-ideal circumstances. The Causal-DRL model exhibited **notable robustness** when exposed to uncertain or adversarial settings. During random perturbations (e.g., sudden power spikes in smart grid CPS or signal loss in traffic systems), traditional DRL policies showed up to **38% degradation** in average performance, while Causal-DRL maintained losses below **12%**. This resilience was largely due to the model's reliance on causal structure learning, allowing it to infer hidden dependencies even when some inputs were corrupted or missing.

4.5 Comparative Discussion and Key Insights

The cumulative findings across all environments highlight that the integration of causal reasoning with deep reinforcement learning creates a **fundamentally different class of adaptive intelligence**. The improvements observed in reward optimization, stability, and convergence are not isolated to numerical gains but represent a **qualitative leap** in how autonomous CPS systems reason, learn, and act.



Musik in Bayern
ISSN: 0937-583x Volume 90, Issue 11 (Nov -2025)
https://musikinbayern.com DOI https://doi.org/10.15463/gfbm-mib-2025-496

Figure 2: Cyber Physical System [25]

Several critical insights emerged from this comparative analysis:

1. **Causal priors accelerate convergence.**
   The causal-guided policy update mechanism allowed the agent to generalize from fewer interactions by inferring unobserved relationships, effectively reducing sample inefficiency a long-standing limitation of traditional DRL systems.

2. **Noise immunity and distributional robustness.**
   The use of structural causal models enabled the system to maintain stable behavior under sensor corruption and non-stationary inputs. The causal reward adjustment discouraged overfitting to transient correlations, leading to sustained performance even when environmental dynamics shifted.

3. **Explainability as a system feature, not a post hoc addition.**
   Unlike existing interpretability methods that analyze trained models retroactively, the causal layer inherently structured decision pathways during learning. This embedded explainability reduced computational overhead and improved auditability in real time.

4. **Generalization beyond seen environments.**
   When tested with unseen configurations (e.g., new load patterns or traffic signal timing sequences), the Causal-DRL model displayed an adaptive response accuracy of **92%**, compared to **77%** for standard DRL. This demonstrates that the model learned transferable, mechanism-based reasoning rather than memorized responses.

5. **Operational Efficiency.**
   Across all test environments, computational efficiency improved by approximately **18%**, primarily due to faster convergence and reduced redundant policy updates. The adaptive causal graph refinement prevented unnecessary learning cycles on non-influential variables.

V. CONCLUSION

The present study demonstrated that integrating **causal inference** with **deep reinforcement learning (DRL)** provides a powerful and interpretable mechanism for enabling autonomous adaptation in complex **cyber-physical systems (CPS)**. Traditional DRL, despite its proven success in dynamic decision-making, operates largely as a correlation-based optimizer, often failing to distinguish between meaningful causal dependencies and incidental environmental patterns. By embedding **structural causal models (SCMs)** within the reinforcement learning architecture, this research introduced a hybrid **Causal-DRL framework** capable of learning not just from observed correlations but from underlying cause–effect mechanisms driving system behavior. Through this integration, the model achieved a dual objective enhancing **policy robustness** under environmental uncertainty while ensuring **decision explainability** across multi-domain CPS applications. The empirical evaluation conducted across three diverse CPS environments autonomous traffic systems, smart grids, and industrial process control validated the efficacy of the approach, revealing significant improvements in reward convergence rates, adaptation speed, and long-term stability when compared to conventional DRL baselines. The causal reward adjustment mechanism served as a critical component, allowing the learning agent to selectively reinforce actions that had demonstrable causal impacts, thus reducing overfitting to spurious or short-term patterns. Moreover, the framework's resilience under stress tests, such as sensor noise, actuator delays, and data loss, established its robustness and reliability in real-world operational settings. Beyond quantitative performance gains, the study's most valuable contribution lies in the **explainability** it affords: each policy decision can be traced through a transparent causal reasoning pathway, bridging the gap between machine intelligence and human interpretability. This feature not only enhances system trust but also enables predictive diagnostics and fault prevention through continuous causal monitoring. The findings underscore that causal reasoning does not merely supplement reinforcement learning but fundamentally reshapes it into a more *scientifically grounded* and *generalizable* form of adaptive intelligence. The Causal-DRL model's ability to maintain stable and rational behavior under non-stationary, adversarial, and data-sparse conditions highlights its potential for wide-ranging applications in safety-

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critical CPS domains, including intelligent transportation, automated manufacturing, energy optimization, and smart infrastructure. It also addresses the increasing industrial and academic demand for **explainable AI (XAI)**, where accountability and traceability are as crucial as efficiency and speed. However, the research also acknowledges existing challenges, particularly the computational complexity associated with dynamic causal graph recalibration and the limitations of current causal discovery algorithms in high-dimensional environments. Future work will focus on optimizing these components through **graph neural networks (GNNs)**, **approximate causal inference**, and **hybrid cloud–edge learning architectures** to ensure real-time scalability. In essence, this study establishes a concrete step toward the evolution of autonomous CPS that can not only act intelligently but also *reason causally*, setting a new benchmark for interpretable, adaptive, and human-aligned artificial intelligence systems.

VI. FUTURE WORKS

Future research will focus on advancing the scalability, efficiency, and real-time deployment of the proposed **Causal-DRL framework** across large-scale, safety-critical cyber-physical systems. One primary direction involves developing **dynamic causal discovery algorithms** that can operate online, continuously updating causal graphs in response to evolving system behaviors without significant computational overhead. Integrating **Graph Neural Networks (GNNs)** with causal inference modules could further enhance structural learning by capturing nonlinear and high-dimensional relationships among system components. Another promising avenue lies in **multi-agent causal reinforcement learning**, enabling distributed CPS entities to share causal knowledge for cooperative adaptation in interconnected environments such as smart cities and industrial IoT ecosystems. Moreover, extending the causal-reward function to incorporate **counterfactual simulations** could allow agents to predict outcomes of unobserved actions, thereby improving decision generalization under uncertainty. Real-world validation will be essential, requiring integration with **edge–cloud computing architectures** to support real-time data processing, low latency, and energy-efficient control. Finally, ethical and safety considerations such as transparency in decision-making and formal verification of causal policies will be prioritized to ensure that causality-driven autonomy remains accountable, interpretable, and aligned with human oversight in future autonomous CPS implementations.

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