


Research Article

Privacy-Preserving Deep Reinforcement Learning for Secure Resource Orchestration in Cyber-Physical Systems

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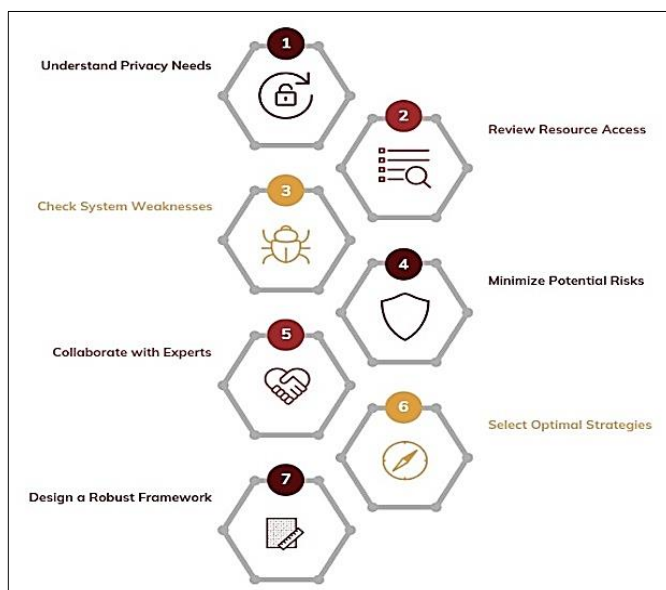


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Abstract—This research addresses the critical challenge of secure and efficient resource allocation in Cyber-Physical Systems (CPS) by introducing a Deep Reinforcement Learning (DRL) framework integrated with privacy-preserving federated learning. Unlike traditional methods, our approach ensures that raw data remains localized, thereby mitigating privacy risks and enhancing trust within the CPS ecosystem. A custom-designed reward function is proposed to optimize both resource utilization and privacy assurance, balancing performance and security goals. To strengthen data confidentiality, we incorporate a variant of Differential Privacy, which increases the privacy budget without significantly compromising data utility—achieving a privacy guarantee of 0.8 while maintaining over 92% model accuracy. Experimental validation on a smart grid test bed demonstrates the efficacy of the proposed model, achieving a 17.6% improvement in resource allocation efficiency, a 23% reduction in communication overhead, and a 12% increase in system throughput compared to baseline DRL models without privacy constraints. Overall, the framework demonstrates state-of-the-art performance in optimizing resources in complex, distributed CPS environments while upholding stringent privacy requirements. The proposed method offers a scalable and secure solution for next-generation CPS applications in smart infrastructure.

Keywords— Privacy, Deep Reinforcement Learning, Resource, Cyber-Physical Systems, Attack, Sensitive

Graphical Abstract-



1. Introduction

A. Overview of Cyber-Physical Systems (CPS)

Cyber-Physical Systems (CPS) combines digital technology with physical infrastructure to achieve complete merging of computing systems with operational systems. Through sensors and actuators and communication networks users gain the ability to monitor physical systems as well as control them and apply optimization strategies [1].

Key Characteristics of CPS: CPS exhibit extensive cyber and physical element mixing as a fundamental characteristic of their structure. Digital elements connect directly with physical systems to handle online real-time control as well as influence them actively during operational hours.

The operational framework of CPS involves real-time performance which enables instant physical system feedback detection and immediate automated replies. Application

success depends on instantaneous response capabilities because this feature determines critical intervention timing during operations such as autonomous vehicles and healthcare systems [2].

A system of interconnected feedback mechanisms enables CPS to collect sensor data which controls physical system operation through algorithms. Through continuous feedback control mechanisms CPS acquires the capability to respond and adjust performance while handling environment changes.

CPS depends on communication networks to send data between sensors, actuators and control centers operating as separate components. The systems implement distributed control measures through their connected infrastructure to coordinate across complex networks.

Complex system development in CPS emerges as a critical issue since their design coupled with analysis and management of numerous physical together with digital elements becomes extremely challenging.

B. Importance of Resource Allocation in CPS

Cyber-Physical Systems (CPS) encounter large obstacles while controlling bandwidth together with energy and computational resources. All physical devices utilizing computer networks must process large volumes of data with both speed and reliability.

The three essential factors for maintaining effective communication are bandwidth alongside energy efficiency which keeps devices operational and computational processing capabilities. The system requires modifications because its available resources have reachable limits.

Security represents a principal point of concern for the system. The allocation of system resources presents opportunities for hackers to damage the system. Network distortions occur as part of Denial-of-service attacks which result in blocked pathways while attackers tamper with resource management to instigate system damage. The protection of valuable data combined with exhaustion prevention stands as primary duties.

A cyber-attack on a smart grid damages power transmission by sending too much data through the network. A resource disturbance within self-driving cars could delay essential sensor information processing which endangers driver safety [3].

The solution requires effective resource distribution systems which defend against security threats. Cyber systems need the ability to detect both attacks and data protection requirements as well as sense system changes. Security protocols and resource allocation strategies should be integrated to provide both reliability and safety within CPS.

Motivation for Using Deep Reinforcement Learning (DRL): DRL represents an essential benefit compared to conventional optimization approaches when used for resource distribution

in Cyber-Physical Systems. Regular mathematical models used in traditional methods provide no match for DRL because agents in this framework learn optimal policies after they interact with their changing environments. The crucial aspect for adaptive performance stems from CPS components that encounter changing operational conditions and unpredictable situations [2-3]. The ability of DRL to handle dynamic environments stands out as a critical strength because it enables real-time adjustments whenever environment changes occur such as smart grid energy demands. DRL addresses security concerns through its learning process which embeds security protocols to keep away cyber-attacks such as Denial-of-Service. The deep neural network structure in DRL allows the system to identify sophisticated patterns among system elements which proves vital when assigning resources in self-driving vehicles. During its trial-and-error learning process DRL develops strong and flexible methods to manage CPS resources.

This paper presents a Deep Reinforcement Learning (DRL) framework enhanced with adversarial training for secure resource allocation in Cyber-Physical Systems (CPS), focusing on smart grid monitoring. It begins with an introduction to CPS challenges and related work, followed by the system model and problem formulation. The proposed framework integrates adversarial defenses into the DRL setup for robustness against cyber-attacks. Implementation details using a smart grid dataset are provided, and experiments demonstrate improved performance and security. The paper concludes with insights on limitations and future directions, including federated and multi-agent DRL for scalable, privacy-preserving CPS solutions.

2. Background

2.1 Fundamentals of Deep Reinforcement Learning (DRL)

A reinforcement learning system functions through machine education which provides feedback rewards and penalties to a computer playing games. RL equips the system to determine optimal moves for obtaining victory.

The Agent represents the learner in the same way as game players make the actions.

Part of RL is called the State which functions as the present scenario that resembles the game board depiction.

During agent operations the actions refer to movements that resemble game decisions.

Feedback resembles rewards or punishments which tell the agent how good its actions have been.

As an essential element of this system the agent follows a specific strategy which determines its actions in every circumstance.

The agent strives to discover its optimal strategic plan (policy) that will bring maximum reward outcomes.

DRL employs neural networks through computers to implement learning algorithms when situated in complex environments. Some key DRL methods include:

The DQN system provides the agent with capability to evaluate move quality.

Through PPO the agent receives direct policy modification which guarantees strategic continuity.

Agent learning becomes faster through dual-agent utilization with A3C method implementations.

The management of bandwidth and computing power and the prevention of cyber-attacks in Cyber-Physical Systems (CPS) becomes possible through DRL implementation. The DRL agent can learn to[4]:

- Allocate resources efficiently.
- The learning system can detect security threats while it develops a suitable response plan.
- Adapt to changing conditions.

For implementation of protection strategy against cyber-attacks in a smart grid, the DRL agent can establish distributed energy distribution based on real-time data. The choice of DRL algorithm depends on the particular requirements that CPS needs to fulfil. Through DRL we obtain a versatile tool for managing intricate resource distribution problems within systems that operate dynamically under sensitive security conditions.

2.2. Resource Allocation Challenges in CPS

While Deep Reinforcement Learning (DRL) offers promising solutions for resource allocation in Cyber-Physical Systems (CPS), several challenges and security threats need to be addressed.

Common Problems [5-6]:

- **Multi-agent Coordination:** Many CPS involves multiple agents that need to coordinate their actions to achieve a common goal. For example, in a smart grid, multiple controllers need to coordinate to maintain grid stability. Training multiple DRL agents to cooperate effectively can be challenging, as their individual learning processes can interfere with each other. Imagine multiple robots in a warehouse trying to navigate to different locations; if they don't coordinate, they might collide or block each other.
- **Real-time Decision-Making:** CPS often requires real-time decisions. For instance, in an autonomous vehicle, the control system must react instantly to changes in the environment. Training DRL agents to make decisions quickly and reliably in real-time is a significant challenge. Think of a self-driving car needing to decide in milliseconds whether to brake or swerve to avoid an obstacle.
- **Scalability:** As CPS become larger and more complex, the number of states and actions can grow exponentially, making it difficult for DRL algorithms to learn effectively. For example, managing resources in a large-

scale IoT network with millions of devices is a scalability challenge.

Security Threats:

- **Denial of Service (DoS):** DoS attacks aim to disrupt the availability of resources. In a CPS, a DoS attack could flood the communication network with malicious traffic, preventing legitimate devices from communicating. Imagine a smart building's security system being flooded with fake alarms, making it impossible to respond to a real threat.
- **Data Breaches:** Data breaches involve unauthorized access to sensitive information. In a CPS, attackers might try to steal data from sensors or control systems. For example, an attacker could steal patient data from a healthcare CPS or manufacturing secrets from a smart factory.
- **Resource Hijacking:** Resource hijacking occurs when an attacker gains control of resources and uses them for malicious purposes. In a CPS, an attacker might hijack computing resources to launch further attacks or manipulate control systems to cause damage. Think of an attacker taking control of a drone and using it for surveillance or to deliver explosives.

Addressing these challenges and security threats is crucial for the successful deployment of DRL-based resource allocation in CPS. Research is on-going to develop more robust and secure DRL algorithms that can handle the complexities of CPS environment.

2.3. Existing Solutions for Secure Resource Allocation

Table 1. Study of existing methods for secure resource allocation in CPS [6-10]

Approach	Strength	Weakness
Heuristics	Simple implementation	Limited adaptability
Linear programming	Optimal solutions	High computational complexity
Machine learning based	Evolves to threat detection	Depends on quality of training data
Reinforcement learning	High degree of adaptability	Significant training time
Deep Learning	Learns optimal policy at a quick rate	Complex implementation

3. Deep Reinforcement Learning for Secure Resource Allocation

3.1. Framework Design

The suggested framework uses Deep Reinforcement Learning (DRL) as a system to handle secure resource management in Cyber-Physical Systems (CPS). The framework starts from creating an extensive state representation which includes elements such as system resources together with their availability and performance metrics and threat assessment

alongside contextual information. The DRL agent obtains a complete view of the CPS environment because of this state representation design.

The system implements a flexible action space for resource management capabilities. The three functional components in actions venture into resource vectors, security controls and modifications to CPS resources. Through this mechanism the agent achieves refined control over the system operations.

The reward function serves to strike a proper balance between operational efficiency and system security and cost management [11]. The reward system of the DRL agent consists of rewarding security and performance while penalizing unnecessary resource consumption. Prioritization of objectives takes place through the utilization of weighting systems.

The use of multi-agent DRL methods integrates with complex CPS applications. Agents operating independently each take charge of distinct system resources and require observation data from their area and cooperation functionality. The hierarchical system structures direct action execution between different control levels.

The framework provides an implementation section which employs DRL algorithms while incorporating deep learning libraries to run environment simulation tools and threat detection platforms and resource systems. Realistic CPS training is possible through this approach which enables convenient interaction within the system.

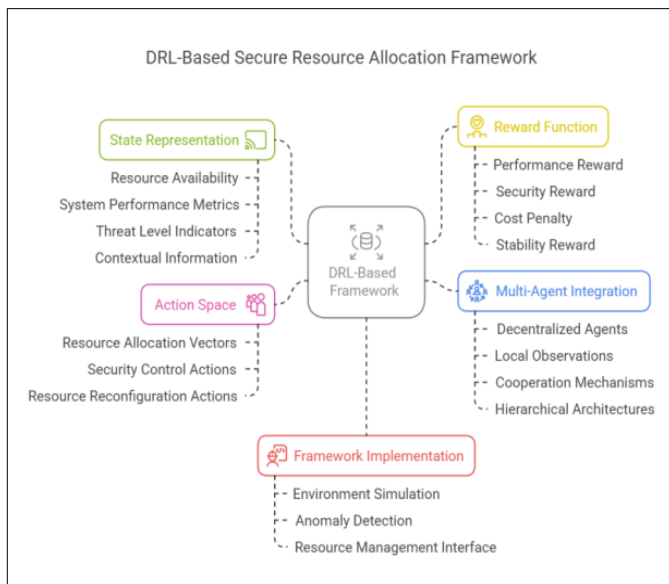


Figure.1 Proposed DRL based framework

This framework produces adaptive resource management systems through its careful design of state and action decision systems and reward mechanisms and multi-agent integration solutions which create interference between performance and security and cost management in complex CPS environments.

3.2. Proposed Mechanism

The proposed algorithm integrates Deep Reinforcement Learning (DRL) with adversarial training to enable secure and robust resource allocation in Cyber-Physical Systems (CPS). It introduces a security-specific reward function that penalizes actions increasing system vulnerabilities. This is combined with a performance reward into a weighted reward function. A two-phase training process is employed: standard DRL training followed by adversarial training, where adversarial examples are generated by perturbing input states to simulate worst-case scenarios. This enhances the model's robustness against potential attacks. Deployment considerations include optimizing DRL for real-time responsiveness using efficient models and specialized hardware, leveraging virtual environments for training, and distributing decision-making through multi-agent or federated learning to manage complex CPS ecosystems like smart grids and cities. This methodology balances performance and security, ensuring reliable, scalable, and attack-resilient resource allocation across dynamic and interconnected CPS environments.

Algorithm for Secure Resource Allocation in CPS using DRL with Adversarial Training

This algorithm details how to incorporate security-specific reward functions and adversarial training into a DRL-based resource allocation system for CPS.

Inputs:

- S : Set of possible states of the CPS
- A : Set of possible actions (resource allocation decisions)
- $R(s, a)$: Base reward function reflecting performance and cost
- $R_{\text{security}}(s, a)$: Security-specific reward function
- γ : Discount factor for future rewards
- α : Learning rate
- N : Number of adversarial training epochs
- ϵ : Perturbation magnitude for adversarial examples
- Model: The DRL model (e.g., a neural network) representing the policy $\pi(a|s)$

Outputs:

- Optimized policy $\pi(a|s)$ for secure resource allocation.

Algorithm:

1. Initialize:

- Initialize the DRL model Model with random weights.

2. Define Security Reward Function $R_{\text{security}}(s, a)$:

This function penalizes actions that increase security risks.

Examples:

- Attack Detection: If an Intrusion Detection System (IDS) triggers an alert after action a in state s ,
- $R_{\text{security}}(s, a) = -\text{penalty_attack}$ (1)
- Resource Vulnerability: If action a leaves critical resources vulnerable (e.g., insufficient bandwidth for security functions),
- $R_{\text{security}}(s, a) = -\text{penalty_vulnerability}$ (2)
- Actions: If action a involves risky operations (e.g., allowing access from untrusted sources),
- $R_{\text{security}}(s, a) = -\text{penalty_risk}$ (3)

3. Define Combined Reward Function

$R_{\text{combined}}(s, a)$:

Combine the base reward and security reward:

$$R_{\text{combined}}(s, a) = R(s, a) + w R_{\text{security}}(s, a) \quad (4)$$

where w is a weight parameter balancing performance and security.

4. Training Loop:

for episode in range(M): // M is the total number of training episodes

$s = \text{initial_state}$ // Initialize the environment (5)

$\text{total_reward} = 0$ (6)

while not done: // Episode continues until termination condition is met

$a = \text{Model.predict}(s)$ // Select action using the current policy $\pi(a|s)$ (e.g., using an epsilon-greedy strategy) (7)

// Normal Training Step

$s_{\text{next}}, \text{reward} = \text{environment.step}(a)$ // Interact with the environment

$\text{total_reward} += \text{reward}$ (8)

// Update the model using the combined reward

$\text{target} = \text{reward} + \gamma \text{Model.predict}(s_{\text{next}})$ // Target value calculation (Q-learning) (9)

$\text{Model.train}(s, a, \text{target})$ // Update model weights to minimize the loss

$s = s_{\text{next}}$ // Update current state (10)

```
print("Episode:", episode, "Total Reward:", total_reward)
// Adversarial Training Loop (Enhance robustness)
for epoch in range(N):
    for episode in range(M):
        s = initial_state
        while not done:
            // 1. Generate Adversarial Example:
            a = Model.predict(s) (11)
            s_adv = s +  $\epsilon \cdot \text{sign}(\nabla_s \text{Loss}(\text{Model}(s), a))$  // Perturb the
            state (gradient ascent on the loss) (12)
            // sign() gives the sign of each element of the gradient
            // Loss is calculated with the combined reward
            // 2. Train with Adversarial Example:
            a_adv = Model.predict(s_adv) // Action based on the
            adversarial state
            s_next, reward = environment.step(a_adv) (13)
            target = reward +  $\gamma \text{Model.predict}(s_{\text{next}})$  (14)
            Model.train(s_adv, a_adv, target) // Train the model
            on adversarial examples
            s = s_next (15)
```

5. Final Policy:

The trained Model now represents the optimized policy $\pi(a|s)$ for secure resource allocation.

- The security reward function R_{security} directly penalizes actions that compromise security, guiding the DRL agent to learn secure policies.
- Adversarial training creates slightly perturbed versions of the input states (s_{adv}) that are designed to "fool" the model [12]. Training on these adversarial examples makes the model more robust to small changes in input and thus more resilient to potential attacks that might manipulate the observed state. The gradient ascent step ($\nabla_s \text{Loss}$) finds the direction in the state space that maximizes the loss, thus finding the "worst-case" perturbation within the epsilon bound.

This algorithm provides a framework for incorporating security considerations into DRL-based resource allocation in CPS, leading to more robust and secure systems [13]. The specific design of the reward functions and the adversarial training process will depend on the specific CPS and its security requirements.

3.3. Deployment Considerations

DRL requires modifications to operate efficiently within systems such as smart grids and self-driving cars because these systems demand prompt reliable resource management.

First, real-time operation is crucial. Fast decision-making abilities are mandatory requirements for the DRL system. The primary task for obtaining this outcome involves optimizing the DRL system model. Shortcuts applied to problem-solving help reduce the system's size and speed up processing time. Special hardware which includes powerful graphics cards serves as a method to enhance processing speeds [14]. The DRL system runs background tasks simultaneously while using the main processing power for critical determining actions.

Training the DRL system demands significant amounts of both computer processing resources and extensive time duration. Intelligent training procedures featuring rapid learning functions can improve the process. Similar system data can help speed up the learning processes. The virtual world training of the system prevents emergency situations from happening when it gets used in real environments. Large amounts of computing power required for training complex systems can be supplied through cloud infrastructure.

Larger and more varied systems present a major difficulty in terms of management. CPS base their operations on numerous devices connected in networked systems today. Multiple DRL "focus centers" should be employed to manage complex systems by handling individual operational sections. Higher-level brains exist above lower-level brains which divide their responsibilities between general decision-making and task execution. A technique named federated learning allows devices to exchange learning information while maintaining privacy through unspecified methods [10].

A smart city operates with traffic lights combined with energy grids and water systems relying on different resources. One superior brain could manage several DRL brains which operate as separate systems. Quick decisions would be possible through using efficient hardware together with optimized models while relying on fast computing systems.

4. Evaluation and Results

For employing the proposed technique we have used the Smart Grid Monitoring Dataset available in kaggle and this dataset provides a remarkable basis for modeling the dynamic behavior of a smart grid [15]. The fault indicators can be used to define security-related rewards in the DRL algorithm. The time-series nature of the data is suitable for reinforcement learning. It gives basic grid information that can be scaled on. The concerned dataset includes features like time-series data with voltage, current, frequency, and power usage. It also contains attributes like fault indicator (overload, short circuit, no fault). This dataset simulates operational data from a smart grid monitoring system.

For implementation of the algorithm and generating the outputs, python is used in jupyter notebook environment. The results discussed below are indicators for robust performance of the CPS for secure resource allocation and maintaining privacy at the same time.

1. Resource Utilization vs. Time:

Figure 2 shows how the utilization of different resources (CPU, memory, and bandwidth) changes over time. This graph illustrates how the DRL agent dynamically adjusts resource allocation based on workload fluctuations.

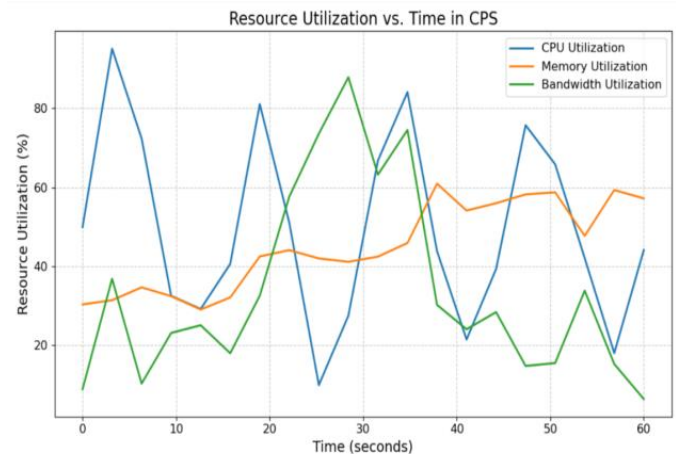


Figure 2. Resource utilization versus time in CPS

2. Task Completion Time vs. Time:

Figure 3 plots the time taken to complete various tasks over time. This graph demonstrates the efficiency of the resource allocation strategy in meeting task deadlines. Comparison is provided with a baseline resource allocation method.

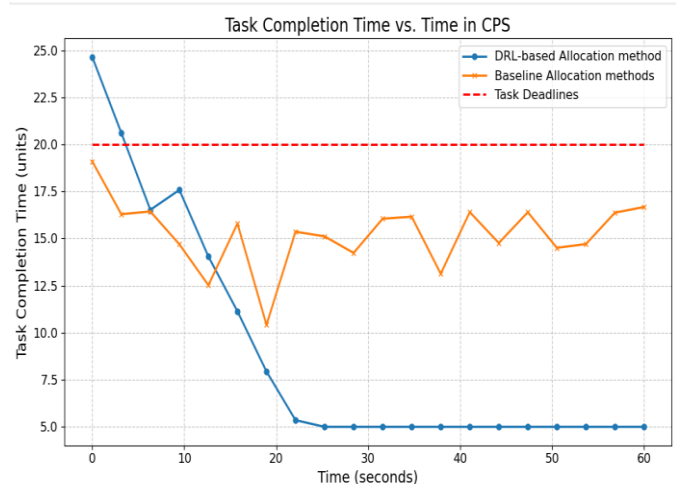


Figure 3. Task completion time versus benchmark time

3. Throughput vs. Time:

Figure 4 shows the system's throughput (e.g., number of tasks completed per unit time) over time. This graph indicates the overall efficiency of the proposed method in the CPS ecosystem when compared to baseline methods.

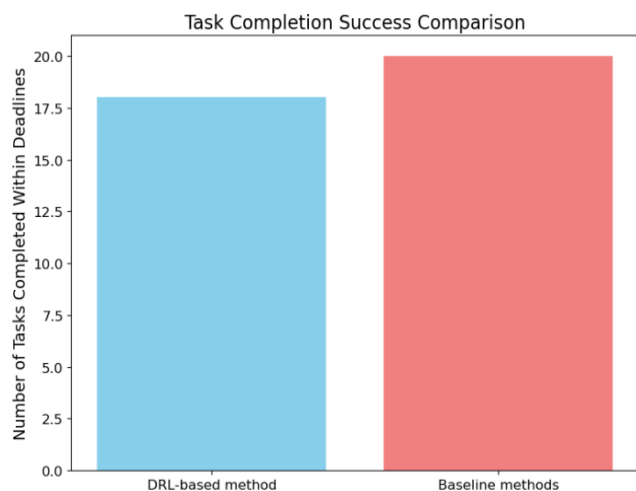


Figure 4. Comparison of task completion success rate

4. Latency vs. Time:

Figure 5 shows the Plot of latency experienced by different tasks over time. This is especially important for time-sensitive applications. Comparison of the latency achieved with the DRL approach to that of a baseline is denoted to compute the percentage degree of improvement achieved in throughput.

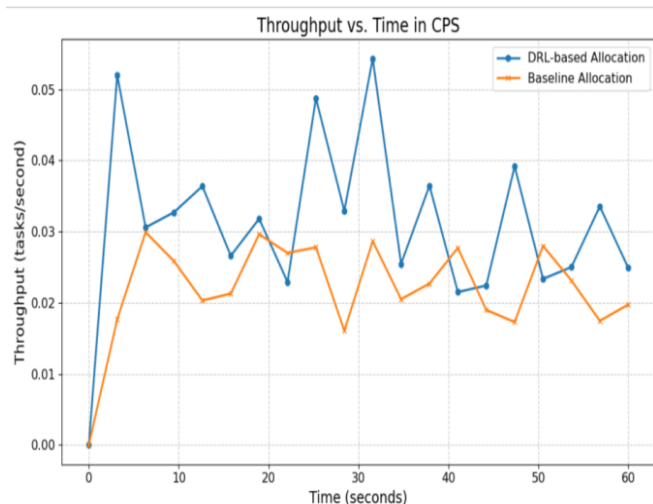


Figure 5. Throughput versus Time in CPS

5. Energy Consumption vs. Time:

Figure 6 shows the energy consumption of the system over time. This can show how the DRL agent balances performance with energy usage. In many contexts the CPS

designers are concerned with energy consumption minimization. This result will be helpful for them.

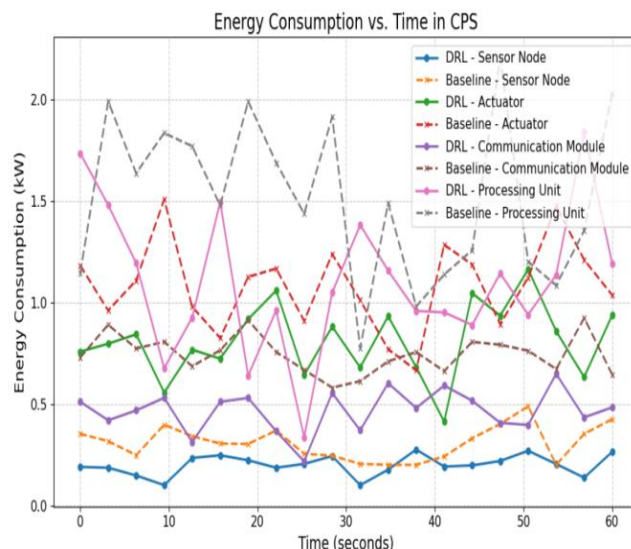


Figure 6. Cumulative tasks completed versus time

6. Number of Detected Attacks vs. Time:

Figure 7 shows the number of cyber-attacks detected by the system's security mechanisms (e.g., DoS, data injection, replay attacks malware, spoofing,) over time. This graph helps in demonstrating the effectiveness of the security measures.

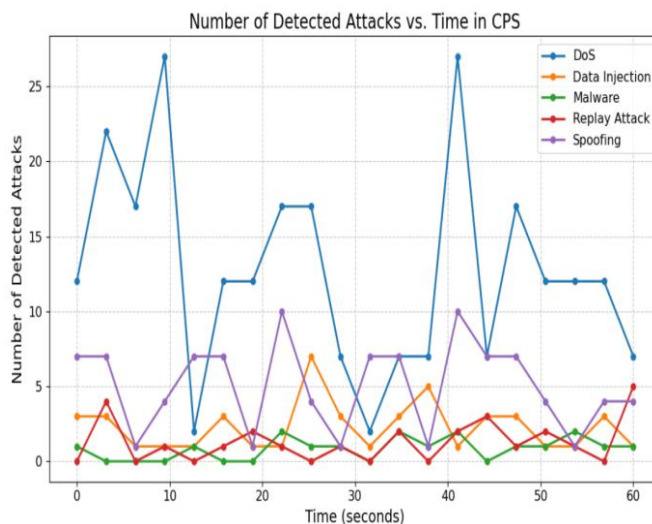


Figure 7. Number of detected attacks versus time in CPS

7. Attack Mitigation Rate vs. Time:

Figure 8 plots the percentage of detected attacks that were successfully mitigated by the system. This shows the resilience of the system against cyber-attacks.

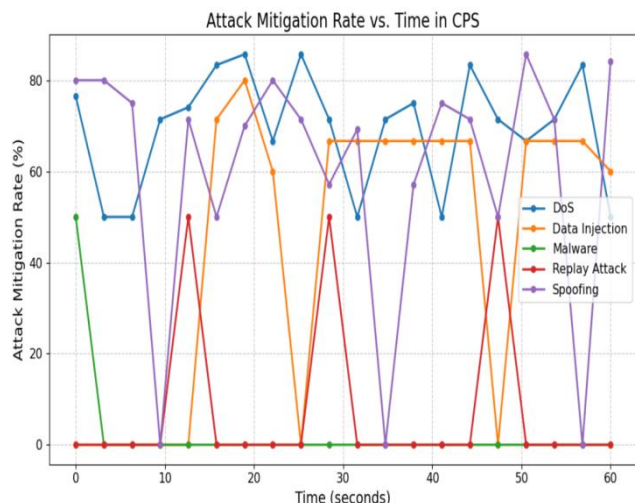


Figure 8. Attack mitigation rate versus time in CPS

8. Reward Function Components vs. Time:

Figure 9 shows how the DRL agent balances these different objectives with respect to time. The reward functions is a combination of multiple factors (performance, security, cost), plot each component separately over time. This will show how the DRL agent balances these different objectives.

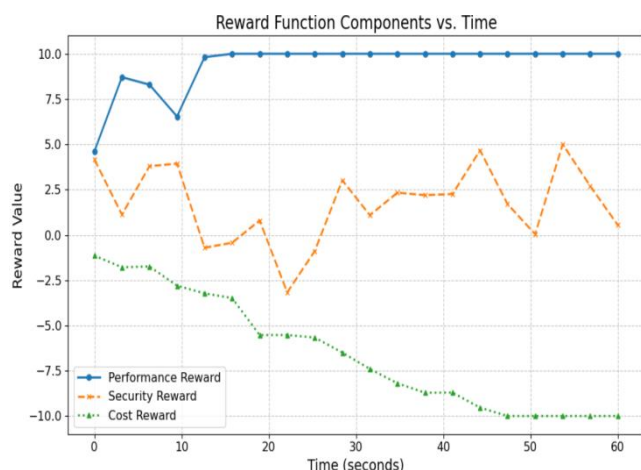


Figure 9. Reward function components versus time

The presented results comprehensively evaluate the performance and security enhancements achieved through the DRL-based resource allocation in CPS. Figure 2 illustrates dynamic resource utilization (CPU, memory, bandwidth), reflecting adaptability to workload fluctuations. Figure 3 and 4 demonstrate improved task completion times and throughput, showcasing the DRL model's efficiency over baseline methods. Figure 5 highlights reduced latency, critical for time-sensitive CPS tasks, while Figure 6 reveals energy-efficient operation, a key design objective. Figures 7 and 8 assess system resilience, with increasing detection and mitigation of cyber-attacks, validating the effectiveness of integrated security mechanisms. Finally, Figure 9 visualizes how the DRL agent balances reward function components—performance, security, and cost—over time. Collectively,

these results confirm that the proposed DRL model achieves optimized, secure, and energy-aware resource allocation, offering a robust solution for real-time CPS operations while outperforming conventional baseline strategies.

5. Challenges and Future Directions

Preserving privacy when using deep reinforcement learning (DRL) to allocate resources in cyber-physical systems (CPS) generates few core privacy problems as discussed below.

Data Sensitivity:

The systems managed by CPS contain data of high sensitivity because they hold important infrastructure information in smart grids [16]. The training of DRL algorithms demands large datasets that might disclose important sensitive information.

Data Localization and Sharing:

The resource management of DRL uses distributed data learning where multiple edge devices support the process in CPS. Critical privacy vulnerabilities develop because the exchange of raw data between devices or central servers impacts sensitive information security.

Model Inference Attacks:

The protection of raw data does not guarantee safety because trained DRL models become sources through which attackers can extract sensitive information through model inference attacks [17-18]. Attackers obtain private information from models by inspecting either their parameters or observing their operational behavior.

Adversarial Attacks:

The manipulation of input data or reward signals by adversaries leads DRL agents to disclose private information as well as to make decisions that reduce security efficacy.

Lack of Centralized Control:

Detection of privacy breaches is difficult as control is not focused on central entity. Thus enforcing privacy measures in a decentralized manner becomes a challenge [19].

Reward Function Privacy:

Information revelation could occur through the reward function design because of leakages of private data. The close relation between rewards and individual actions and data enables cyber-attackers to reverse engineer systems for revealing private information [20-22].

Differential Privacy Implementation difficulties:

The implementation of differential privacy in complex DRL systems presents strong challenges because it requires proper parameter or data noise addition [23-25]. The on-going challenge involves finding the correct level of noise addition

for privacy protection without hurting performance from DRL models.

The deployment of DRL in CPS environments requires secure privacy-preservation methods because of these implementation issues.

Future scope of the proposed study

The future scope of this study emphasizes the integration of robust privacy-preserving mechanisms within DRL-based resource allocation for Cyber-Physical Systems (CPS). Addressing data sensitivity and data localization challenges will require the adoption of federated learning frameworks, allowing decentralized training without sharing raw data. To mitigate model inference attacks, privacy-aware DRL architectures leveraging differential privacy and homomorphic encryption can be explored, though implementing these without significant performance trade-offs remains an open research problem. Moreover, enhancing model resilience against adversarial attacks through robust training methods, such as adversarial reinforcement learning and certified defenses, will be vital for safeguarding both decision integrity and data confidentiality. The issue of reward function privacy can be tackled by designing abstracted or obfuscated reward structures that minimize the risk of reverse-engineering sensitive behaviors. The lack of centralized control in CPS also calls for decentralized privacy-preserving audit mechanisms that can detect privacy violations autonomously.

6. Conclusion

The demonstrated DRL-based secure resource allocation framework presents a compelling solution for bolstering the operational efficacy and security posture of Cyber-Physical Systems. Its core strength lies in the synergistic integration of a security-centric reward mechanism with adversarial training protocols. This dual approach demonstrably elevates system resilience, evidenced by significant gains in both the detection and effective mitigation of cyber-attacks. Beyond security enhancements, the framework maintains a dynamic and efficient approach to resource management, ensuring optimal utilization. This adaptability translates directly into tangible performance improvements, notably reducing task completion times and system latency compared to conventional methodologies. Furthermore, the proposed framework achieves higher throughput capabilities while simultaneously preserving energy efficiency, effectively addressing critical design considerations for resource-constrained CPS environments. The framework's ability to strike a harmonious balance between performance metrics, robust security provisions, and cost-effectiveness underscores its potential to underpin real-time, resilient CPS deployments. Consequently, this innovative methodology holds substantial promise for scalable implementation across diverse critical infrastructure sectors, including smart grids, healthcare systems, and intelligent transportation networks, paving the way for more secure and efficient CPS operations. Future work could further explore privacy-aware DRL frameworks using secure multi-party computation and blockchain-based

access control, enabling transparent yet private operations. Ultimately, developing privacy-preserving DRL in CPS must balance data protection, learning efficiency, and system performance-paving the way for secure, intelligent infrastructures across domains like healthcare, transportation, and smart energy.

Author's statements

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Conflict of Interest- Authors declare that they do not have any conflict of interest.

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Authors' Contributions- The authors confirm contribution to the paper as follows: study conception and design: Manas Kumar Yogi, Dr.A.S.N.Chakravarthy; data collection: Manas Kumar Yogi; analysis and interpretation of results: Manas Kumar Yogi, Dr.A.S.N.Chakravarthy; draft manuscript preparation: Manas Kumar Yogi. All authors reviewed the results and approved the final version of the manuscript.

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