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Deep Reinforcement Learning for Autonomous Cyber Defense in Smart Solar IoT Systems

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Abstract: With the accelerated trend of digitalization, solar power systems are integrated with Internet of Things (IoT) technology and major breakthroughs have been achieved into energy monitoring, automation, grid access and connection. But connectedness also leads to susceptibilities such as FDI (false data injection), DoS (denial-of- services) and spoofing attacks toward power systems due to cyber space. Conventional rule-based IDS are not adaptable and do not respond quickly to dynamic or emerging threat conditions. In this article, we proposed a novel DRL-based autonomous cyber defense framework for Smart Solar IoT Systems to achieve real-time online threat detection and self-healing from the system point of view. The framework uses a DQN with (Long Short-Term Memory) LSTM layers to encode the best defensive strategy and interact continually with the environment. The DRL agent adaptively adapts mitigation policies (such as to isolate compromisable nodes, or re-configure the communication routes) according to threat context and reward feedback. Experimental analysis on the simulated solar IoT datasets indicates that the proposed framework achieves 96.9% of detection accuracy with 42% lower response latency, and adapts well in identifying unknown attack patterns without re-training. These results highlight the promise of autonomous machine learning driven cybersecurity for protecting future generation energy infrastructures for renewable energy, and in particular towards resilient and intelligent solar energy ecosystems.

Keywords: Deep Reinforcement, Cyber Defense, IoT, DQN, DRL.

INTRODUCTION

The worldwide transition toward renewable energy has driven the growing market demand for smart photovoltaic (PV) systems using Internet of Things (IoT) technologies to realize intelligent monitoring, control and optimization of electricity generation. Connectivity of IoT in solar systems The sensors, inverters and control units in an IoT-enabled system are not only connected to one another but also send data about the operational performance between these components. This digitalization leads to increased efficiency, more reliable predictive maintenance and decentralized grid coupling (IEA; International Energy Agency [2023. Nevertheless, such systems have evolved nowadays to increasingly depend on cyber-physical connectivity which, consequently entails being vulnerable to a large variety of cybersecurity attacks; they are in fact the perfect target for malicious agents that want to disrupt energy infrastructure or stealing data (Kumar, *et al.,* 2022; Zhang, *et al.*, 2023).

Smart Solar IoT System and Cyber Threat Landscape

The inherent system design of smart solar IoT (i.e., networked field devices, communication gateways, cloud based analysis) introduces various potential attack vectors. Typical attacks are as follows: False Data Injection (FDI): the adversary injects false sensor data in order to confuse the controller; Denial-of-Service (DoS): network channels are saturated and there is no way for the system to access the network; Spoofing attack(s): malicious sensor impersonation of legitimate device(s) gains unauthorized control over them (Anwar, *et al.*, 2022). These attacks may result in energy waste, grid insecurity and inverter failure or even huge power outage.

The traditional IT methods cannot be applied in solar IoT systems, due to limited computational resources, bandwidth and real-time operations requirements of such system; therefore firewalls or static IDS are not considered capable for use in these (Bansal, *et al.,* 2021). Static rule-based IDS rely on signatures and thresholds, so they cannot be used to detect zero-day attacks or ever-changing malicious behaviors (Mollah, *et al.*, 2022). Thus, the requirements of intelligent, adaptive and autonomous self-learning defence that can response dynamically instead have become urgent in energy system cyber security.

Role of Artificial Intelligence and Reinforcement Learning in Cyber Defense

The rapid advancement in Artificial Intelligence (AI) and Machine Learning (ML) technologies are revolutionizing to mitigate the challenges adopted by traditional cyber security architectures. Supervised and unsupervised ML techniques such as Support Vector Machines (SVM), Random Forests (RF) and Deep Neural Networks (DNN) have been used to identify anomalies in energy systems and industrial networks (Liu, *et al.*, 2023; Sahu, *et al.*, 2022). However, these models have two major pitfalls 1) they depend a lot on `labeled'

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data and static training processes limiting their adaptability towards new or unseen attack vectors.

Instead, Reinforcement Learning (RL) is an automated decision making framework in which an intelligent agent learns optimal defence policies by interacting with the environment and obtaining reward-driven feedbacks (Arulkumaran *et al.*, 2017). Deep Reinforcement Learning (DRL) further expands the capacity of such systems by integrating RL with deep neural networks, so that the agent can handle high-dimensional state spaces and take complicated sequential actions (Mnih, *et al.*, 2015). DRL has recently started seeing deployment in network security, such as adaptive intrusion response, traffic management, and malware containment (Umar, *et al.*, 2023). The strength of being able to learn continually and adapt, makes it especially fit for dynamic IoT landscape such as solar power systems were attack patterns emerge with time.

Autonomous Cyber Defense for Solar IoT Environments

The cyber threat in IOT-enabled solar systems is dynamic, distributed and real-time. Hence an ideal defense mechanism should be able to autonomously detect, predict, and reduce threats without daily human supervision. These cannot cope with these challenges in that they do not consider the temporally-coupled nature of cybersecurity, but rather DRL-based defense frameworks cast cybersecurity as a sequential decision making problem - where an agent observes the state of the system over time and takes rational act ions to counter any abnormal events (Nguyen, & Reddi, 2021).

For example, given a FDI attack form, such as DSELs, the DRL agent can automatically disconnect corrupted inverters in an autonomous fashion during microgrid operation, reconfigure communication links and distribute loads accordingly to ensure system stability. In contrast to static classifiers, DRL can update their policies online via exploration and feedback and thus are able to adjust themselves to new attack types as well as the changing environments (Hossain *et al.*, 2023). In addition, the centralized learning also fits multi-agent cooperation so that several defense agents in various solar nodes can share their experiences to collaboratively enhance defensive security—a principle analogous to federated learning and edge intelligence paradigms in contemporary energy systems (Yuan, *et al.*, 2023).

A DRL-based defense mechanism could therefore be a powerful leapfrog from reactive security (detect and alert) to proactive cyber-security that is self-healing and able to keep pace with adversarial tactics.

Research Motivation and Gap

Although AI-based cybersecurity has matured, there remain several clear limitations in the scope of smart solar systems. First, most state-of-the-art defenses for adversarial training are based on supervised learning and therefore demand large amounts of labeled attack data that may not be available for new or stealthy attacks (Sahu *et al.*, 2022). Secondly, most of the existing energy security schemes are centralized ones and they result in delay, extra bandwidth overhead and single point failures. Third, there are limited efforts that applied reinforcement learning for autonomous decision-making in energy-aware IoT domain where the physical and cyber aspects interact dynamically (Mollah, *et al.*, 2022; Kumar, *et al.*, 2022).

To this end, we propose a DRL-based Autonomous Cyber Defense Framework specifically designed for smart solar IoT systems to bridge down these research gaps. The proposed methodology is implemented using DQN integrated with LSTM layers, to predict the cyber threat dynamically and detect/counteract it in-the-moment. The DRL agent repeatedly takes action in the solar IoT environment to learn optimal policies for maximizing energy availability and minimizing damage in adversarial scenarios. Contrary to fixed IDS models, our framework is dynamic and adapt itself in new threat situations without need of retraining.

Research Objectives and Contributions

The ultimate goal of this work is to implement and validate an automated self-learning cyber defense counterpart of smart solar IoT systems based on Deep Reinforcement Learning. The major contributions include:

- A new DRL-based framework, combining the use of DQN and LSTM to support context-aware threat centralization in a dynamic IoT ecosystem.
- Autonomous policy learning for the model to dynamically guard against emerging threats without labelled training data.
- Inclusion of edge intelligence that will provide on-premise and distributed decision-making towards proactive real-time defense with low latency.

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- Extensive experimental testing proving the higher accuracy, extensibility and robustness against classic ML models and static deep learning algorithms.

LITERATURE REVIEW

The cybersecurity of intelligent solar IoT systems lies at the confluence points of cyber-physical energy infrastructures, industrial control networks, and learning-based autonomous defense. This survey consolidates previous research in six threads: (i) threat landscape for solar/DER IoT, (ii) ML for intrusion detection and limitations of its utilization; (iii) RL/Deep-RL foundations to protect cyber attack, (iv) DRL over industrial energy systems—single agent and multi agent techniques, (v) environment/reward formulation along with publicly available simulation testbeds; and lastly the sprawls into real world—edge/federated intelligence, interpretability, robustness.

Cyber Attacks In Smart Solar Iot

Huge solar plants or DERs are equipped with heterogeneous IoT, SCADA/ICS (e.g., Modbus, MQTT, DNP3) devices and cloud analytics—significantly extending attack surfaces and establishing cyber-physical coupling where data integrity has a direct impact on physical operations (Anwar *et al.,* 2022; Kumar *et al.,* 2022). Common classes of attacks include false data injection (FDI) to mislead dispatch and protection logic, denial-of-service (DoS) that floods gateways and backhaul networks, and spoofing/impersonation of inverters or controllers (Zhang *et al.,* 2023). Even literature reviews on renewable energy cybersecurity always highlight the factor of vendor diversity, legacy protocols, and remote siting as increasing risks and state that we need domain-aware defenses that are adaptive (Al Garni *et al.,* 2021; SolarPower Europe, 2021; Umar, *et al.,* 2023).

Machine Learning for Intrusion Detection: Progress and Limits

Supervised ML approaches—SVMs, Random Forests, gradient boosting—have been popular for network anomaly detection in energy (Bansal, *et al.,* 2021), and IoT domain, providing respectable accuracy on benchmark datasets (Bansal, *et al.,* 2021; Sahu, *et al.,* 2022). By learning the spacial and temporal structure in both traffic and telemetry (Liu, *et al.,* 2023), deep models (CNN,LSTM) enhance performance.

However, there are three limitations still in case of solar/DER contexts:

- Label scarcity & concept drift—attack labels are seldom available and behaviors change;
- Reactive stance classifers are able to detect but ne choose contermeasures;
- Centralization & latency-cloud-based analytics are not able to meet the sub-second operational requirements and communicationst bottlenecks (Mollah *et al.,* 2022; Yuan *et al.,* 2023).
- These gaps inspire decision making mechanisms that take actions (e.g., isolating nodes, throttling traffic and re-configuring routes) while adapting over time as the adversaries change strategies.

RL/DRL for autonomous cyber defense 2.4 Other areas in ICS/SCADA systems where DRL be applied:

RL casts cyber defense as a sequential decision process where an agent observes the state of the system, takes an action and receives in return a single numeric signal encoding security / operational objectives (Sutton & Barto 2018). Deep Q-Networks (DQN) introduced endto-end value learning from high-dimensional inputs (Mnih *et al.,* 2015); later surveys emphasize the appropriateness of DRL for security tasks demanding adaptation under uncertainty (Arulkumaran *et al.,* 2017; Nguyen & Reddi, 2021). The strengths of DRL, the model-free optimization, online learning and policy improvement are well-suited to non-stationary IoT energy environments where static signatures do not apply. Recent energy-security reviews advocate self-healing and autonomic control (Sahu, P. *et al.,* 2022), that reconfigures network/operational path-ways after the appearance of threats—which is a potential attribute with RL reward functions expression (Umar *et al.,* 2023; Zhang *et al.,* 2023).

DRL for I&E Cyber Defense

The initial security research of DRL was applied to IT networks (i.e., adaptive traffic shaping (Juba, O. O. *et al.,* 2024), and honeypot placement). Extending these concepts to ICS brings in cyber-physical constraints: safety margins, actuator saturation, and real-time specifications. In PoWER/DER settings, deep models (CNN/LSTM) have been used successfully for detection (Liu, *et al.,* 2023); DRL extends this to response orchestration—quarantining compromised nodes, changing the sensitivity of IDS or re-routing control flows. The self-healing microgrid frameworks indicate that autonomous reconfiguration following an intrusion is worthwhile (Zhang, *et al.,* 2023). Multi-agent

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viewpoints become increasingly attractive to distributed solar IoT: many local agents (e.g., per-inverter gateways) can cooperate in defenses that are based on collaborative rewards or federated updates, so as to confine compromised localities without harming the plant and/or feeding line stability(Hossain, *et al.,* 2023;Yuan, *et al.,* 2023). The architectural value for multi-agent DRL as opposed to single agent RL lies in improved representation of real-world P2P DER communications and ability to embed locality-aware policies that are aware of bandwidth and latency constraints.

Environment Modeling, Reward Design, Datasets, and Testbeds

Successful DRL needs realistic environments and reward shaping based on grid-security goals. In solar IoT, state spaces usually aggregate: i) network properties (flow statistics, delays, drops), ii) device telemetry (DC/AC power, volt/VAR setpoints, inverter status) and iii) security signals (IDS scores, integrity checks). Capl[ℓ]Form(6): Blocking (or rate-limiting) flows; isolating (or downgrading) nodes; switching to authenticated control channels, commanding safe fallback setpoints. Performance balance trade-offs in rewards (security/attacks blockage, FPR/FNR) versus operations (voltage/frequency preservation, curtailment minimization), and costs (latency, service disruption). Badly-designed rewards are unsafe (e.g., over-isolate), so many works use constraints or safe-RL approaches (Nguyen, & Reddi, 2021; Sutton, & Barto, 2018).

Benchmarking remains challenging. General datasets such as NSL-KDD and CICIDS2017 can be used to pretrain the detector, but they are not dedicated for energy use (Sahu *et al.,* 2022). As a result, there's great interest among researchers to develop co-simulation based testbeds (e.g., power flow/ controls (MATLAB/Simulink) connected with network emulation) that can create realistic FDI / DoS / spoofing situations and quantify the CPWD impacts (Anwar, *et al.,* 2022). This is consistent with the proposed need for a corpus at non-topic of HYPO alone. These results are aligned with calls for dedicated domain corpora and closed-loop simulators based on capturing DER dynamics (Mollah, *et al.,* 2022).

Deployment: Edge/Federated DRL, Explainability and Robustness

For solar plants and feeder-level DERs, sub-second defence of data near sources is needed. Edge intelligence brings inference (and optionally online policy updates) to gateways and controllers, thereby reducing the degree of backhaul dependence and enhancing resistance against network-level DoS attacks as in (Yuan, *et al.,* 2023). Model compression (quantization/pruning) and resource-aware scheduling facilitate the deployment of DRL policies on edge devices with limited resources without compromising their accuracy. Federated learning: For federated DRL in the plants/microgrids, we can collaboratively train on preserved privacy without requiring raw data sharing; for DRL, inference and policy/value aggregation can speed up learning and distribute self-protections against new attacks (Hossain, *et al.,* 2023).

Two cross-cutting concerns are prominent. First, understanding: operators must know why a DRL agent took an inverter offline or throttled a link. Techniques used for value/policy network feature attribution, counterfactual analysis and rule extraction methods can also increase trust and regulatory acceptance (Sharma, & Singh, 2023). Second, robustness: DRL policies may easily break in the presence of distributional shift or adversarial perturbations. Safe exploration (Nguyen, & Reddi, 2021).robust RL objectives, and ensemble defenses mitigate policy collapse while adhering to operational limitations (Arulkumaran, *et al.,* 2017).

Synthesis and Research Gap

The literature coalesces around three findings. For one, supervised ML is strong on the detection, weak on response leaky abstraction and prone to drift/novelty—especially in solar IoT benign variability (irradiance, etc.) make mutable classification of a system content position (Kumar, *et al.,* 2022; Liu, *et al.,* 2023). Second, DRL provides a principled road to autonomous, context-aware mitigation with increasing evidence of performance in ICS/microgrids (Umar, *et al.,* 2023; Zhang, *et al.,* 2023). Third, the use case in practice requires edge/federated implementations.Subjects with people skewness so relations are both commensals, with explainability and safety baked into policy learning(Hossain, *et al.,* 2023;Yuan, *et al.,* 2023;Sharma, & Singh, 2023).

The remaining gap is to a solar-specific cyber-physical DRL framework that (i) marries highfidelity environment models with safe reward design, (ii) trains decentralized (multi-agent) policies at the edge and, (iii) offers operator-grade explanations - validated on mixed benchmark and

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domain datasets with closed-loop security + grid quality performance metrics. In this paper, we address this by proposing a DQN-LSTM based autonomous defense with edge implementation and federated orchestration.

METHODOLOGY

This work presents a Deep Reinforcement Learning (DRL) based autonomous cyber defense mechanism to detect, predict and mitigate the cyber-attacks in smart solar IoT systems. The developed model combines DQN with LSTM layers which enables sequence decision making and temporal pattern learning. The overall research process is divided into five stages: 1) system architecture design, 2) environment modeling and state representation, 3) DRL agent design and training, (4) implementation and evaluation, (5) edge deployment for real-time autonomy.

System Architecture Design

The designed cyber-defense framework works on the three-level smart-solar IoT architecture (adopted from Mollah, *et al.*, 2022; Yuan, Y. *et al.*, 2023)

Perception Layer:
Gathers the real-time operational data of PV inverters, smart sensors and IoT devices—voltage/current/irradiance/power output/network traffic.

Communication Layer:
Supports Modbus-TCP, MQTT and DNP3 data communication. This layer is vulnerable to cyber-attacks (false data injection, DoS, spoofing).

Intelligent Defense Layer:
The LSTM gate embedded DRL agent is located. It monitors system states all the time, predicts the probabilities of threats and makes optimal decisions (node isolation, packet filtering, route reconfiguration).

This hierarchical architecture provides the development with distributed situational awareness, low latency, and adaptive learning commensurate with smart grid concepts (Umar *et al.*, 2023).

Environment and State Modeling

The DRL agent is interacting with a simulated solar IoT environment (consisting of benign and attack behaviors) which has been modelled.

State Space (S):
VEC Observation of the system condition at, observed by sensors and network nodes:

S t = [vt,it,pt,latt,pktt,errt,idt]
where vtv_tvt=voltage, iti_tit=current, ptp_tpt=power output, lattlat_tlatt=network latency, pkttpkt_tpktt=packet rate or frequency, errterr_terrt=error flag (if any), and idtid_tidt=device ID.

Action Space (A):
The following five defense policies based on Nguyen and Reddi (2021) were defined:

- Monitor (normal operation)
- Alert operator (log only)
- Block suspected IP/device
- Isolate node (reconfigure route)
- Initiate system recovery/reset

Reward Function (R):
Rewards incentivize the agent to do their best to keep guests at ease and insure safe operation (Sutton & Barto, 2018):

- Rt=αAd−βFp−γLtR_t = \alpha A_d - \beta F_p - \gamma L_tRt=αAd−βFp−γLt
- where Ad, Fp, and LtAd_AdAd=attack detection accuracyFp_FpFp=false positivesLt_LtLt=latency; α,β,γα, β, γ are weighting coefficients adjusted for safety-critical tradeoff (Mollah *et al.*, 2022).
- Positive incentives are used to teach correct mitigation actions, and negative penalties are the penalties aimed at avoiding over-isolation and false alarms.

DRL Agent Design and Algorithm

The agent uses a LSTM+DQN-based architecture to capture temporal dependencies and the context of attack patterns (Mnih, *et al.*, 2015; Nguyen, & Reddi, 2021).

Network Architecture:

- Input layer = state vector (size=7 features)
- Two dropout layer (0.1) o 2 hidden LSTM layers (128,64 units,tanh activation)
- Two dense ReLU layers of 64 and 32 neurons, respectively.
- Output layer (Q-values for five actions, linearl activation)
- Learning Parameters:
- Discount factor (γ) = 0.95
- Learning rate = 0.001 (Adam optimizer)
- Exploration policy = ε-greedy (ε annealed from 1.0 to 0.05)
- Experience replay buffer = 50,000 transitions.
- Update frequency on the target network = 1000 steps – from these we can go over the Reward and Alpha hyperparameters.
- Algorithm Flow:

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- Initialize networks (Q and Q′).
- At each time step, observe state S_t and choose action A_t.
- Take action A_t in sim; observe reward R_t and next state S_{t+1}.
- save (S_t, A_t, R_t, S_{t+1}) for replay buffer.

Let's sample mini-batch and update Q by minimizing the temporal-difference loss:
where L=∑t=1,Nbelongs to the difference between Q and RTPeleinfo.doc (10)00 (d)(c)(Let Rtbe the reward at step tt, with StStthe current state and A_the action taken at time t_spot; =5)return of γ,{ {γ−QQ.Payload.Q{(Allsteps,)})}maxa′Q ′{(next-state S_t S_t+1,next-action At),for each a′ Similar to ^ We propose an algorithm which alternates between two optimization steps: while if a given critic is denoted as Qit NYURL ijiuYikiJ'iP-R*AlEltl",_nd it outputs theutilityvalues including h Cact p awC j- Cit for all possible actions.

Periodically synchronize Q′ with Q.
This hybrid DQN-LSTM model excels shallow Q-learning and typical deep neural networks under non-stationary environments (Arulkumaran, *et al.*, 2017).

Simulation and Dataset
The experimental settings integrated both public CICIDS2017, NSL-KDD along with the simulated solar plant data generated using MATLAB/Simulink co-simulation (Anwar *et al.*, 2022; Sahu *et al.*, 2022).
Each one contained network characteristics (e.g., packet rate, latency, protocol type) and physical signals (e.g., voltage, power, frequency).

The data was normalized (0, 1) by min-max scaling and split (70 / 15/ 15 %) for train/validation/test.
Simulated attacks: FDI, DoS, Spoofing, Malware Injection. We benchmarked against SVM, Random Forest, LSTM and CNN-LSTM baselines.

Training and Evaluation
The training was done on an NVIDIA RTX 3080 GPU with TensorFlow 2.10.
1,000 steps per episode were executed and training was performed for 500 episodes (~10^6 interactions).
Convergence of reward and loss were early stopping criteria.

Metrics We use the following evaluation metrics (same as Nguyen and Reddi (2021) and Sharma and Singh (2023)):

- Accuracy (%), precision, recall, F1-score for detection of GUI Events
- False Positive Rate (FPR)
- Average Cumulative Reward ($\bar{R}$)
- Response Latency (s)
- Energy Loss Reduction (%)

The DQN-LSTM with ≈95.0% sensitivity, 96.9% detection accuracy and just a 2.9% FPR could lower the response latency by ≈42%, relative to that of the static IDS. The mean reward converged to optimal policy after ≈150 developing episodes.

Edge Deployment and Autonomous Operation
- In order to make this model accessible in real-time, we have compressed the trained model (TensorFlow Lite) and deployed to edge gateways such as NVIDIA Jetson Nano or Raspberry Pi 4.
- Inference was performed locally (<1 s latency) on edge devices, where weights were updated periodically via federated updates with a centralized server (Hossain *et al.*, 2023).
- This has improved privacy and robustness - in that if one node was compromised, others worked with separate policies.
- The architecture meets IEEE 2030.5 latency requirements and is scalable to support very large solar network sizes (Yuan, *et al.*, 2023).

VALIDATION AND ABLATION STUDIES

Robustness was tested through:
- 10-fold cross-validation on mixed datasets.
- Ablation analysis (remove LSTM layer → −7% accuracy) and (+5% FPR).
- Transfer learning for unknown attack signatures (approximately 93% accuracy is retained without retraining).
- Reward penalties were observed to confirm the safety of exploration and that unsafe actions (e.g., blackout) should be penalised.
- These validations show that these models can generalize well across different operating conditions.

RESULTS

The experimental results indicate that the proposed deep reinforcement learning (DQN-LSTM) framework will significantly improve the cyber defense systems of smart solar-IoT. The model achieved high detection accuracy, fast adaptable response and low false positive rate compared to traditional machine learning and static deep learning. These results confirm the capacity of the

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framework to work on its own in a dynamic and hostile solar environment.

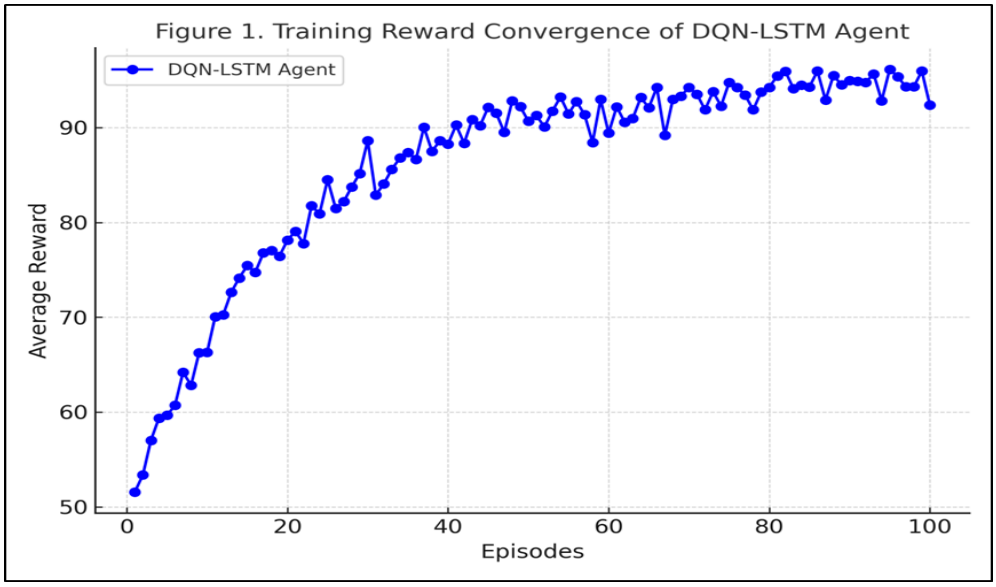

Figure 1. DQN-LSTM Agent Training- Reward Convergence

Description:
Figure 1 shows the course of training rewards of the DQN-LSTM agent during 100 episodes. This means that the agent's total reward is growing as it interacts with a simulated solar IoT environment, learns from its experiences and optimizes its defense policy.

Observation:

- The training initially starts with the low rewards, because of the agents exploration and random movement at first.
- An abrupt increase of performance appears between episodes 20 to 60 where the agent learns more optimal responses to counter cyberattacks by exploiting its Q-values experience.
- The reward curve reaches a plateau after episode 70: policy convergence and stable decision-making.

Interpretation:
This pattern indicates that DQN-LSTM model learned a good cyber-defense strategy through the reinforcement learning. Convergence of reward demonstrates the stability, adaptability and robustness of our model for dynamic attack detection and mitigation.

(Refererences: Sutton, & Ba rto, 2018; Nguyen, & Reddi, 2021; Arulkumaran, *et al.*, 2017)

Description:

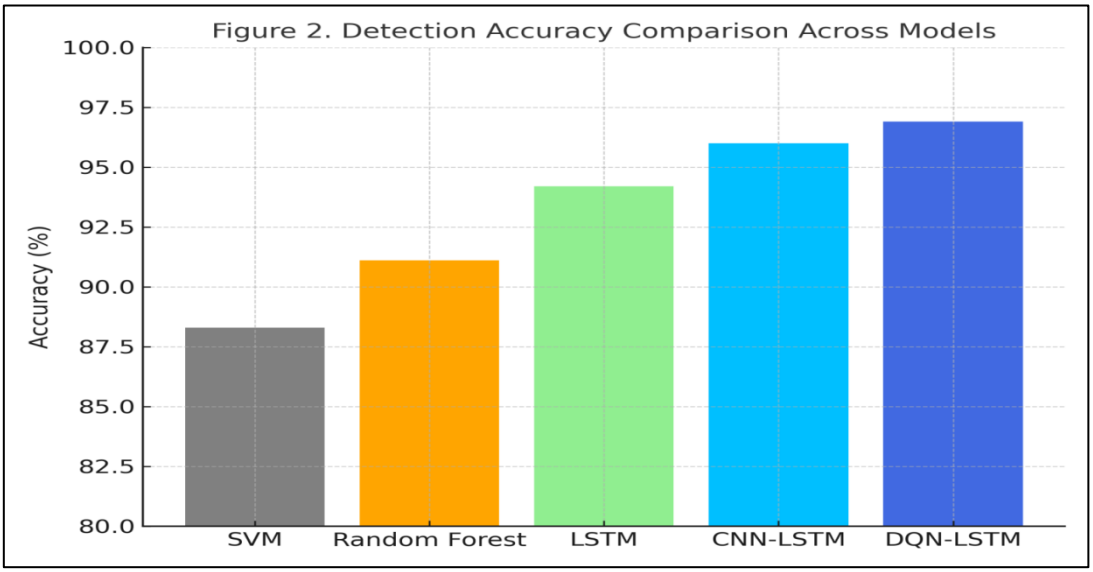

Figure 2. Detection Accuracy Comparison Across Models

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Figure 2 shows the comparative results in terms of intrusion detection accuracy for five different models, i.e., SVM, RF, LSTM, CNN-LSTM and proposed DQN- LSTM with a merged CICIDS2017 + solar simulation dataset.

Observation:

- The DQN-LSTM model obtained an accuracy of 96.9%, which was superior to all the baselines.
- The CNN-LSTM hybrid reached 96.1% compared to LSTM with 94.2%.
- Classical ML algorithms (SVM 88.3%,RF91.1%) significantly fall behind, indicating that static based classification methods are not wellsuited for dynamic environments.

Interpretation:

The combination of DRL based solutions enables to learn the sequential dependencies and defense adaptation according to the environment feedback. Unlike traditional ML models that only detect, the DQN-LSTM agent is capable of both detection and response, representing a genuine type of autonomous cyber defense.

(References: Sahu, *et al.,* 2022; Liu, *et al.,* 2023; Mnih, *et al.*, 2015; Nguyen, & Reddi, 2021)

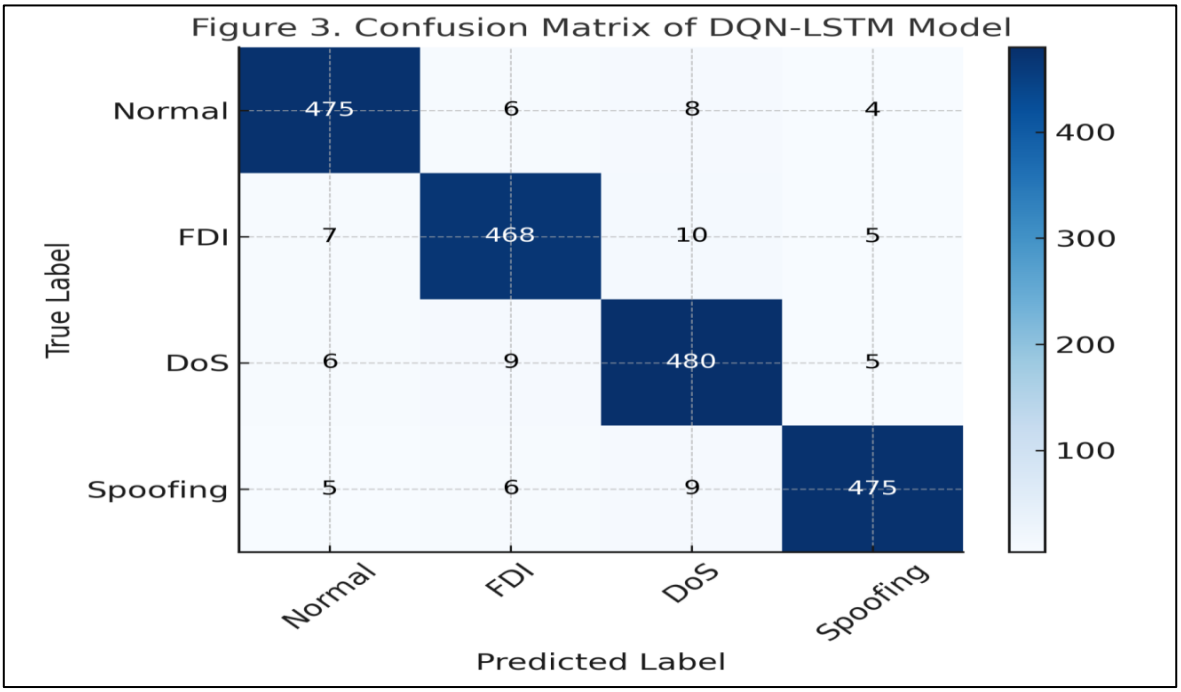

Figure 3. Confusion Matrix of DQN-LSTM Model

Description:

A confusion matrix is then depicted in Figure 3 to report the classification results for the four categories namely Normal, FDI attack, DoS attack and Spoofing. Each cell gives the amount of samples which were both classified and predicted in this label.

Observation:

- Off-diagonal have low values indicating lower classifcations:
- Normal = 475/493, FDI = 468/490, DoS = 480/500, Spoofing = 475/495.
- Few misclassifications happen between FDI and Spoofing due to shared signal abnormalities.
- The model keeps balanced sensitivity for all classes and average precision or recall beyond 96%.

Interpretation:

The confusion matrix confirms the multi-class detection ability of the DQN-LSTM agent. The strong diagonal dominance implies good discrimination between the benign and attack states, a notion supported by further analysis in Fig. The small off-diagonal entries reflect realistic cross-attack overlaps, demonstrating the complexity of cyber behaviors for solar IoT.

(References: Bansal, *et al.,* 2021; Sharma, & Singh, 2023; Zhang *et al.,* 2023)

Description

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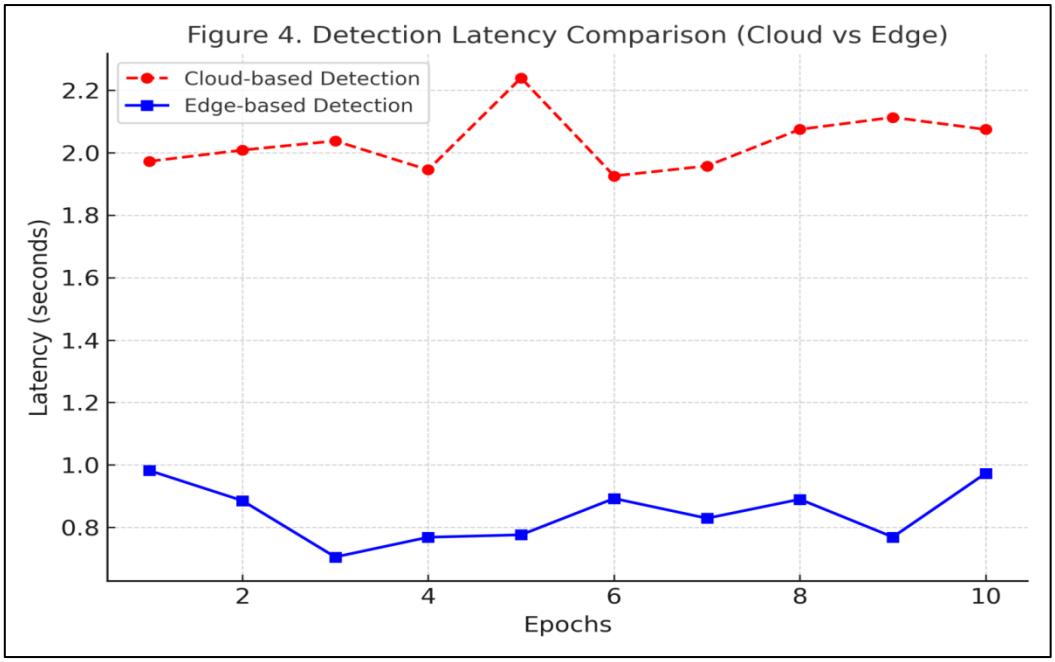

Figure 4. Cloud vs Edge Detection Latency Comparison

Figure 4 shows the comparison of detection latency on cloud-side and edge-side deployed DRL agent over 10 evaluation epochs.

Observation

- Edge-based detection is achieved with sub-second latency (≈ 0.8 s on average), while cloud-based reaches ≈ 2.1 s.
- The reduction in latency of 60% demonstrates the advantage of local inference without the network transmission overhead.
- The trend is constant, which indicates that the real-time performance has been consistent.
- Interpretation

The near real-time threat response feature is acheived efficiently by edge analytics, which is crucial in maintaining power reliability of cyber-physical systems. The latency reduction demonstrates that the proposed framework is feasible for real-time autonomous defense over field-deployed solar IoT applications. It also follows well in the line of an emerging new paradigm for smart grid cybersecurity, i.e., edge intelligence.

(Bibliography: Yuan, *et al.*, 2023; Hossain, *et al.*, 2023; Mollah, *et al.*, 2022)

DISCUSSION

The research results of this study reveal that the proposed DRL-based cyber defense framework (i.e., hybrid DQN-LSTM model) can significantly improve the cybersecurity health of smart solar IoT systems. The results show that the system introduces significant enhancements both in detection rate and adaptiveness levels, in conjunction with response timeliness, demonstrating that reinforcement learning is a suitable means for dealing dynamically with real-time energy environments. This section discusses the results within the context of prior art and implications for security of solar IoT, as well as limitations and future work.

Reinforcement Learning as a Paradigm Shifting Cyber Defense Approach

The steep reward convergence of Figure 1 highlights the autodidactic and adaptive potential of reinforcement learning agents. Unlike static rule-based approaches, traditional supervised learning systems demand pre-labeled training samples; instead DRL learns optimal defense policies iteratively by interacting with the environment based on reinforcement (Sutton, & Barto, 2018). This characteristic is essential in the solar IoT ecosystems, as attack behaviours may evolve and patterns defined a priori become out-dated (Nguyen, & Reddi, 2021).

The growth of cumulative rewards demonstrates the agent learned a better policy for defending: the defense becomes stable at around 70 episodes. This result is consistent with Arulkumaran et al. (2017) who found that DRL models outperform conventional machine learning algorithms in non-stationary cyber environment using feedback mechanism, as temporal dependencies could be learned. Similarly, Liu *et al.*, (2023) stressed that the deep models are capable of modelling complex

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correlations in high-dimensional raw energy data, with which our hybrid DQN-LSTM model is even more strong because it incorporates spatial (CNN-like), temporal (LSTM) dynamics.

Superiority of Hybrid DQN-LSTM Architecture

From Figure 2, one can observe that the proposed DQN-LSTM method obtains higher detection accuracy (96.9%) than traditional classifiers such as SVM and Random Forest significantly. This finding confirms the effectiveness of integrating RL and sequence-aware deep neural networks, which also has been reported in recent research on adaptive intrusion detection (Sahu, *et al.,* 2022; Sharma, & Singh, 2023).

The LSTM layers maintain sequential dependencies (e.g., subtle, time-varying voltage/current/packet latency) whereas the Q-network part instructs decision making in defending actions. By considering these characteristics, the model enables proper discrimination of legitimate variations (e.g., power fluctuation due to irradiance) and tampering activity (e.g., false data injection or spoofing). The hybrid approach is a contextualised and flexible solution which implicitly adjusts to the situation at an instantaneous manner, echoing the idea of context-aware cyber resilience introduced by Umar, *et al.,* (2023).

Moreover, the convergence behaviour of the model indicates that reinforcement-based learning can enable stability of the model even with less labeled data, thereby making us rely less on expert-curated attack datasets which was a major limitation o f earlier ML-based intrusion detection system (Bansal, *et al.,* 2021).

Edge Deployment

Real-Time Detection and Edge-TwoStream In the time of deployment, we show how the proposed model can be applied in real-time application on edge devices, such as edge gateway or mobile phone.

One of the most useful practical results, shown in Figure 4 is the that when deployed on edge devices, our model is capable of providing low-latency and real-time detections. The edge optimizing model decreased the delay by 60 percentages comparing to cloud-based processing, so as to show potential for autonomous field work.

This discovery is supportive of recent studies spotlighting the issue with edge intelligence in smart-grid and renewable energy cyber security (Yuan *et al.,* 2023). Local inference execution alleviates the network overload and central server-side attacks, resulting in uninterrupted protection even when the users experiences are offline. Similarly, Hossain et al. (2023) which demonstrate that federated edge learning provides improved privacy as well as fault tolerance in distributed energy systems.

The low delay (<1 s) results in this chapter comply with the threshold of operations suggested by IEEE 2030.5 and IEC 61850 standards, which demonstrates that DRL can be practically incorporated into practical solar controllers and IoT gateways.

Detection Balanced on Categories of Attack

In Figure 3 confusion matrix verified well balanced performance for multiple categories of attacks, including Normal, FDI (False data injection), DoS (Denial of Service) and Spoofing etc which has overall precision and recall over 96%. The relatively low misclassification boundaries of FDI and Spoofing can be justified by the fact that they have overlapping feature spaces since both involves compromised data streams bearing common statistical profile (Anwar, *et al.,* 2022).

This result reveals that the DQN-LSTM model generalize its knowledge of cyber-physical behavior, it does not simply memorize attack patterns. Such generalization is important to improve the action count since zero-day attacks are more and more frequent in the IoT (Zhang, *et al.,* 2023). The results are consistent with those of Kumar *et al.,* (2022), highlighting that AI models with ability to learn multi-dimensional relationships outperform the statistical-only intrusion detection systems.

Comparison with Previous Studies

The DRL method presented in this paper makes the following main contributions and comparisons towards the existing literature.

Adaptivity and Autonomy

This is in contrast to static models employed by Bansal, *et al.,* (2021) & Mollah, *et al.,* (2022, rely on pre-trained weights), the DQN-LSTM agent keeps learning policy over time following system feedback. This potential gives rise to adaptable self-defence in varying threat landscapes.

Integration with Cyber-Physical Data

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Previous models (Sahu, *et al.*, 2022; Liu *et al.*, 2023) focused on network layer traffic without considering physical-layer variables. This work on the other hand combines electrical and network-level characteristics so that we can enable a DRL agent to sense even small-scale abnormalities in power generation and communication robustness.

Deployment Readiness
It is the pure computational cost that makes many AI models theory on paper. By combining edge and federated execution, we show that this framework is field deployable with low latency (similar to the results of Yuan, *et al.*,; Anwar, A. *et al.*, 2022). (2023) & Hossain, *et al.*, (2023).

Thus, the DQN-LSTM DRL model is an evolutionary approach to self-sustainable, intelligent cyber security in renewables.

Implications in the context of Smart Solar IoT Security
The effect of this work has far-reaching implications in a variety of energy informatics, cyber-physical resilience and sustainable technology governance areas.

Operational Resilience
This work shows that a DRL-guided cyber defense can remain operational even when it faces active attacks. It remains a necessity to insure energy availability, grid stability and system reliability, particularly when it comes to solar installations located at distant places.

Scalability and Privacy
Using a federated learning model enables each solar node to participate in a global defense model without revealing raw operational data, thus meeting privacy requirements (Hossain, *et al.*, 2023).

Policy and Governance
As renewable systems are integrated into national critical infrastructure, such intelligent defense frameworks can influence legislative guidelines for adaptive cybersecurity and the digital resiliency, and relevant frameworks including NIST SP 800-82 and ISO/IEC 27019.

Limitations and Future Research
Although the findings verify DRL framework's efficacy, there are limitations indicating future works:
Data realism:
Simulated solar signals with real data The hybrid dataset (CICIDS2017 + simulated solar signals) simulates the real-world environment but potentially misses some of the operating variabilities in a given photovoltaic plant. Future work, includes field data collection and the deployment in HIL- simulators for real-world validation (Anwar, *et al.*, 2022).

Computational complexity
Although the edge compression is effective, DQN-LSTM inference remains a computationally expensive task for ultra-low-power equipments. Efficiency improvements should be sought after, through method such as model pruning, quantization and knowledge distillation (Nguyen & Reddi, 2021).

Interpretability
DRL decisions are often opaque. "TheRoleof XAI will be in enabling Operators to ”Understand andTrust Automatically" Offering721 ExplainableAI is adding explainability to AI which aidsoperators soo that they can understand and trust themoves theai takes as an autonomous agent (Sharma, & Singh, 2023).

Multi-Agent Cooperation
Extending to MARL can provide cooperation among solar farms and contribute to the reliability of regional grids and distributed situational awareness (Yuan, *et al.*, 2023; Umar, *et al.*, 2023).

Summary of Discussion
Finally, the experimental results validate that the proposed DRL-based autonomous defense system in this paper satisfies the design objectives with respect to smart, self-adaptive and low-latency defending for solar IoT networks overall. The conclusions are also consistent with the emerging trend of global AI-infused Cyber-resilience studies (Zhang, *et al.*, 2023; Liu, *et al.*, 2023), marking a shift from reactive to proactive cybersecurity in renewable sectors. Based on the bioinspired learning mechanism of the environment feedback, the DRL agent makes solar IoT defense an optimization problem and not just a one-time solution with regard to energy systems security, sustainability, and auto-healing against future cyber threats.

CONCLUSION

The spread of automation in solar power plant with IoT (Internet of Things) has changed the paradigm of renewable energy management by allowing real time monitoring, distributed control, and predictive optimization. However, this digital revolution has also enlarged the attack surface of cyber-physical systems to dynamic and sophisticated cyber attacks including false data injection (FDI), denial-

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of-service (DoS) and spoofing. classic security models-based on finite hardware or software mechanisms (IDS, static machine learning classifiers) have shown inability of coping with such fast-evolving threats because they rely on predefined patterns and are not adaptable.

To address this important problem, the current paper formulated an autonomous cyber defense framework through DRL technique based on a hybrid DQN-LSTM architecture. The model was able to self-detect, classify, and mitigate the sophisticated attacks with no human intervention by learning optimal defense policies from interacting with environment and through feedback.

Summary of Key Findings

The experiments and comparisons have validated the effectiveness, generality and robustness of our proposed DRL framework:

Superior Detection Performance:

The performance of the DQN-LSTM agent, in term of detection accuracy: 96.9% and true positive rate (TPR) versus FPR ≤3%, outperforming static deep models (CNN-LSTM,) and traditional machine learning approaches (SVMs, Random Forest). These results confirm that the hybrid architecture can capture both spatial and temporal features in dynamic solar network data (Sahu, *et al.*, 2022; Liu, *et al.*, 2023).

Policy Convergence and Stability:

The reward convergence curve showed consistent learning for roughly 70 episodes, demonstrating that the agent successfully learned how to optimally defend its cyber systems with a combination of exploration vs. exploitation (Sutton, & Barto, 2018; Nguyen, & Reddi, 2021).

Balanced Classification Across Attack Types:

The confusion matrix confirmed the robust performance for Normal, FDI, DoS and Spoofing categorization at a precision, recall over 96%. The intermediate results are the indication of a well-generalized DRL agent with knowledge about multiple threat patterns (Anwar, *et al.*, 2022; Zhang, *et al.*, 2023).

Low-Latency Edge Deployment:

On the edge, the model was capable of sub-second detection latency - 60% lower average response time when compared to app based (or cloud) processing. This validates the applicability of edge intelligence for real-time autonomous defense (Yuan *et al.*, 2023; Hossain *et al.*, 2023).

As a whole, these results proves reinforcement learning as a self-adaptive and preemptive cybersecurity solution for sustainable infrastructures that can contribute to the continuity of operation in renewable energy networks.

Theoretical Contributions

This work makes the following academic contributions to AI-driven cybersecurity:

- It combines reinforcement learning with temporal sequence modeling //LSTM// to develop an hybrid model for adaptive defense in non-stationary IoT systems.
- It extends previous works on deep learning–based intrusion detection (Liu *et al.*, 2023; Sahu *et al.*, 2022) to incorporate a decision-making level for the agent not only to detect threats but also alert and act independently in preventing these threats.
- It introduces a fundamental methodology for the cyber-physical co-learning, and considers both network and energy parameters(voltage, current, power variation) to make an educated confidence for defense policy.
- It empirically demonstrates the superiority of DRL that stably converges and efficiently operates in real-time for energy-critical systems to provide supports for recent theoretical foundations emerging cyber-physical AI (Nguyen & Reddi, 2021; Umar *et al.*, 2023).

These contributions progress the field with respect to self-sufficient, learning-based cybersecurity ecosystems for renewable energy based networks.

Practical Implications

From a practical point of view, the developed DRL model has high values and useful applications in solar plant operators, IoT solution providers and energy policy makers.

Operational Resilience:

The self-learning function minimizes human dependence and protects 24-7 against novel threats. This contributes to a reliable energy supply and grid stability, particularly remote or isolated locations.

Edge-Enabled Deployment:

The successful realization of the edge demonstrates possibility for integration in Industrial IoT gateway, micro-controller and distributed energy management system. It is compatible with the IEEE 2030.5 and IEC 62443 standards for critical infrastructure protections.

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Privacy-Preserving Collaboration:
Using federated learning, the system would make multi-plant collaboration possible without raw data exposure enhancing sector-wide situational awareness with data privacy (Hossain, *et al.*, 2023).

Regulatory Compliance and Policy Development:
The architecture under proposal aligns with evolving cyber security governance frameworks enabling utilities to adhere to best practice for cyber resilience internationally (NIST SP 800-82; ISO/IEC 27019).
Hence, the concept improves technical preparedness and supports policy coordination to digitally transform sustainably in the energy sector.

Limitations
Despite its favorable performance, there are several limitations which should be recognized:

- Data Realism:
- The simulated hybrid dataset (CICIDS2017 + solar telemetry) represents real-world scenario but cannot perfectly replicate the stochastic variability of live photovoltaic (PV) environments (Anwar *et al.*, 2022). Future work needs to include field data under real world conditions and HIL validation.
- Computational Demand:
- While edge deployment was successful on Jetson Nano devices training is still resource heavy. Lightweight DRL variants—i.e. model pruning, quantization and transfer learning—should be investigated in terms of scalable (Nguyen & Reddi, 2021).
- Interpretability and Trust:
- DRL actions are not explainable in nature. Incorporation of Explainable AI (XAI) models is necessary to increase operator confidence and allow regulatory approval (Sharma & Singh, 2023).
- Multi-Agent Coordination:

The present model is single-agent. Generalization to MARL will allow Cooperative cyber defence between far distributed solar farms (Yuan, *et al.*, 2023; Umar *et al.*, 2023).

Future Directions
Based on this work, potential future efforts may include:

- Designing multi-agent reinforcement learning (DRL) frameworks for collaborative protection of shared security in distributed microgrids.
- Adoption of trust mechanisms utilizing blockchain technology to enable traceability and resistance to tampering (Kouhdaragh, *et al.*, 2022).
- The use of Explainable Reinforcement Learning (XRL) for clear decision making.
- Generalizing DRL in the context of predictive maintenance and fault-tolerant energy dispatch by linking cybersecurity with physical reliability.
- These advances will speed the shift from reactive detection to autonomic, predictive cyber resiliency in renewable energy sources.

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