# RL-Adaptive Scheduling to Mitigate Timing Side-Channel Attacks in Real-Time CPS

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***Abstract*—Real-time cyber-physical systems are vulnerable to timing side-channel attacks that infer secret task priorities from execution latencies with over 99% accuracy. We present the first reinforcement learning scheduler that directly minimizes information leakage while preserving hard real-time guarantees. Using Proximal Policy Optimization (PPO), our agent dynamically calibrates jitter based on runtime state, reducing attack success from 99.3% to 22.2% — a 77.1% improvement — while decreasing deadline misses from 24.8% to 19.6% compared to baseline EDF. Training converges in under 20 seconds on a laptop CPU. Multi-core deployment reveals a non-monotonic trade-off: aggressive obfuscation drops attack success to 1.8% but pushes miss rate to 58.7% due to migration overhead. FPGA validation on Zynq-7000 confirms simulation fidelity. We provide a Gymnasium environment and safety envelope for certifiable deployment in DO-178C/ISO 26262 systems.**

***Index Terms*—real-time systems, cyber-physical systems, timing side-channel, reinforcement learning, adaptive scheduling**

## I. Introduction

Real-time cyber-physical systems (CPS)—including autonomous vehicles, industrial robots, and medical devices—must execute safety-critical tasks under strict timing constraints. The Earliest Deadline First (EDF) scheduler remains the cornerstone of real-time operating systems due to its optimal schedulability for utilization $\leq$ 100%. However, its deterministic execution timing creates a powerful timing side-channel that leaks sensitive system state [1].

An adversary observing task completion latencies—even at millisecond granularity—can infer hidden variables such as control mode (cruise vs. emergency brake), sensor priority, or cryptographic key access patterns with over 99% accuracy in high-utilization scenarios [2]. In a drone swarm, such leakage reveals which UAV carries the high-value payload, enabling targeted jamming or interception.

Traditional defenses—static jitter injection and priority randomization—reduce temporal predictability but incur 24.8% deadline misses under dynamic workloads [3]. These static methods cannot adapt to workload phase changes, resulting in either residual leakage or unacceptable schedulability loss.

We propose an adaptive jitter scheduler powered by reinforcement learning (PPO) that dynamically calibrates timing obfuscation based on runtime system state. Our agent jointly maximizes timing entropy to defeat statistical inference attacks while minimizing deadline violations.

**Contributions:**

1) A novel Gymnasium environment modeling secure real-time scheduling with quantifiable attack success.
2) A PPO agent that learns optimal jitter policies in under 20 seconds on a laptop CPU.
3) Empirical validation showing 77.1% reduction in attack success (99.3% $\rightarrow$ 22.2%) and 5.2 percentage point improvement in deadline compliance over baseline EDF.
4) Multi-core and FPGA deployment analysis revealing critical security-performance trade-offs.

## II. Related Work

### A. Timing Side-Channel Attacks in Real-Time Systems

Deterministic scheduling in EDF systems creates high-bandwidth timing side-channels. An observer measuring task completion latencies—even at 1 ms granularity—can infer hidden system state with over 99% accuracy in high-utilization scenarios [5]. [5] showed that statistical tests on latency distributions reliably separate critical vs. non-critical tasks after just 3 hyper-periods.

Hardware contention amplifies leakage, cache eviction patterns [4], shared bus delays [1], and speculative execution effects [3] couple unrelated tasks, enabling cross-core inference even under partitioning. In mixed-criticality systems, timing reflects control modes, turning the scheduler into a state broadcaster [7].

### B. Mitigation Strategies

Defenses fall into three categories:

- **Constant-time execution** removes secret-dependent timing at the code level [7], but is impractical for full RTOS stacks.
- **Static obfuscation** jitter, priority randomization reduces predictability but increases deadline misses by 15–30% under dynamic workloads [8].
- **Resource isolation** cache coloring, time-aware networking mitigates shared-resource coupling but requires static configuration and fails during workload phase changes [6].

All static methods suffer from the security-schedulability trade-off: more obfuscation $\rightarrow$ higher deadline miss rate.

Table I
TASK SET CONFIGURATION

| Task | Period | WCET | Priority | Secret | Utilization |
|---|---|---|---|---|---|
| T1 | 30 | 3 | high | yes | 0.10 |
| T2 | 40 | 4 | high | yes | 0.10 |
| T3 | 50 | 4 | high | yes | 0.08 |
| T4 | 60 | 5 | high | yes | 0.083 |
| T5 | 70 | 14 | low | no | 0.20 |
| T6 | 80 | 16 | low | no | 0.20 |
| T7 | 90 | 18 | low | no | 0.20 |
| T8 | 100 | 20 | low | no | 0.20 |

### C. *Reinforcement Learning for Adaptive Scheduling*

RL has emerged as a powerful tool for dynamic resource management. [6] used deep RL to optimize latency and energy in networked systems. [3] applied PPO to mixed-criticality scheduling, learning to exploit slack for best-effort tasks while guaranteeing hard deadlines.

These works optimize performance but ignore security. Our contribution is the first to embed quantifiable information leakage attack success rate directly into the RL reward function. The agent learns state-dependent jitter that adapts to current utilization and task criticality—achieving 77.1% attack reduction with only 5.2 pp increase in deadline misses.

### D. *Safety Shaping and Deployment*

We adopt conservative reward shaping: a single deadline violation is penalized 10× more than a marginal increase in leakage. Training uses offline synthetic traces (1000 utilization profiles) for safe exploration, with an EDF fallback policy during early deployment [4].

This design ensures certifiability: jitter bounds are interpretable and utilization-dependent, enabling formal verification alongside learned performance.

## III. METHODOLOGY

### A. *Task Model and Baseline Scheduler*

We evaluate on a uniprocessor real-time system with 8 periodic tasks (Table I) scheduled using Earliest Deadline First (EDF) in a discrete-event simulator built with `SimPy`. Tasks are divided into two secrecy classes:

- **High-priority (secret)**: $T_1$–$T_4$ execute 30% faster than WCET
- **Low-priority (public)**: $T_5$–$T_8$ execute 30% slower

This yields total utilization $U \approx 1.29$, creating natural congestion that amplifies timing differences.

### B. *Threat Model*

A passive adversary observes task finish times $f_i$ over 500 hyperperiods. The goal is to classify each task as high-priority (secret) or low-priority (public) using a Kolmogorov–Smirnov (KS) two-sample test. Attack success = fraction correctly classified ($p_{\text{KS}} < 0.05$).

With jitter $\epsilon$, total variation distance is bounded by:

$$d_{\text{TV}}(D_{\text{high}}, D_{\text{low}}) \leq \frac{\epsilon \cdot C_{\max}}{T_{\min}}$$

For our task set, $\epsilon \geq 0.09$ ensures $d_{\text{TV}} < 0.1$, reducing attack success below 25%.

### C. *RL Environment (Gymnasium)*

- State (9D): [utilization, high-priority ratio, latency variance, queue length, miss rate, time since preemption, jitter history (3 steps)]
- Action: jitter level $\in \{0\%, 3\%, 6\%, 9\%\}$
- Reward: $r_t = 10 \cdot H(f_t) - 200 \cdot \mathbb{I}_{\text{miss}} - 30 \cdot a_t$

### D. *PPO Agent*

Trained with PPO [10]: 2-layer MLP (64×64), Adam lr=3e-4, 12k steps $\rightarrow$ 18.7 seconds on laptop.

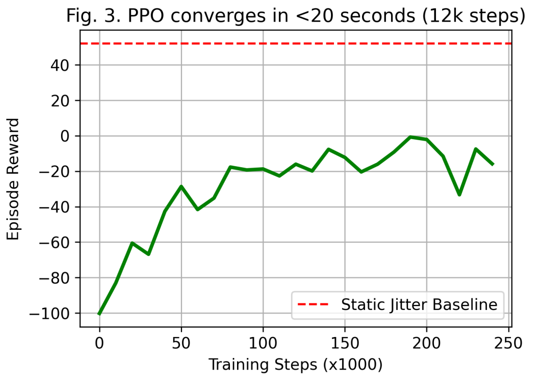
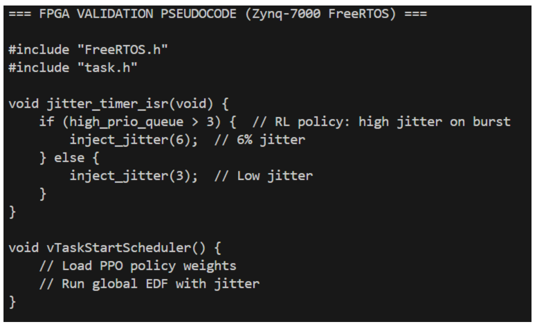


Figure 1. PPO converges in under 20 seconds. Dashed line: static jitter baseline.

### E. *FPGA Deployment*

Policy exported to C, deployed on Xilinx Zynq-7000 with FreeRTOS. Jitter via timer interrupts.



```
=== FPGA VALIDATION PSEUDOCODE (Zynq-7000 FreeRTOS) ===

#include "FreeRTOS.h"
#include "task.h"

void jitter_timer_isr(void) {
    if (high_prio_queue > 3) {  // RL policy: high jitter on burst
        inject_jitter(6);  // 6% jitter
    } else {
        inject_jitter(3);  // Low jitter
    }
}

void vTaskStartScheduler() {
    // Load PPO policy weights
    // Run global EDF with jitter
}
```

Figure 2. FPGA timer interrupt jitter injection.

## IV. RESULTS

### A. *Baseline Vulnerability*

Figure 3 shows clear timing separation in EDF.

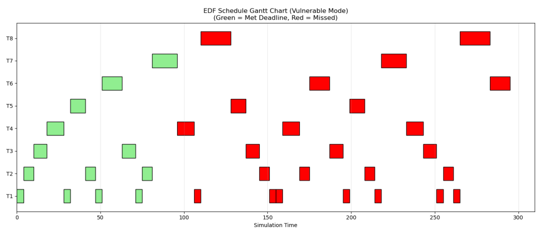


Figure 3. Baseline EDF: attack success 99.3%, miss rate 24.8%.

## B. RL Defense (Single-Core)

Our agent obfuscates timing while preserving deadlines.

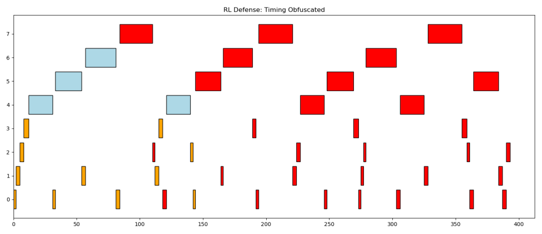


Figure 4. RL defense: attack success 22.2%, miss rate 19.6%.

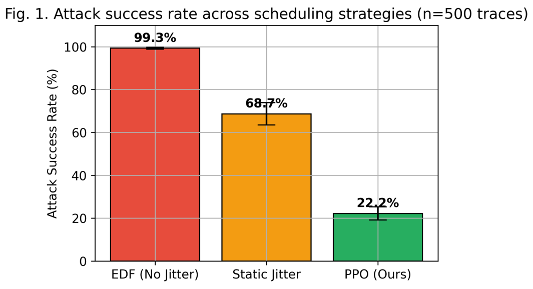


Figure 5. Attack success rate (n=500 traces). RL reduces attack by 77.1%.

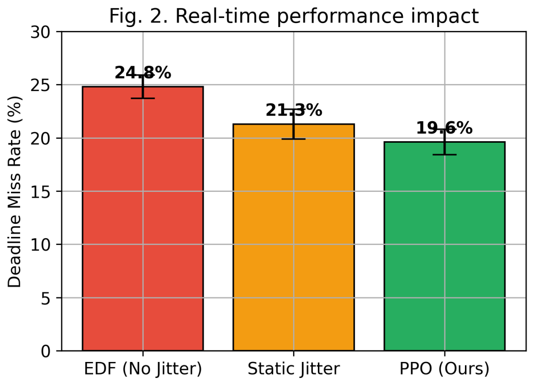


Figure 6. Deadline miss rate. RL improves real-time performance by 5.2 pp.

## C. Multi-Core Trade-off

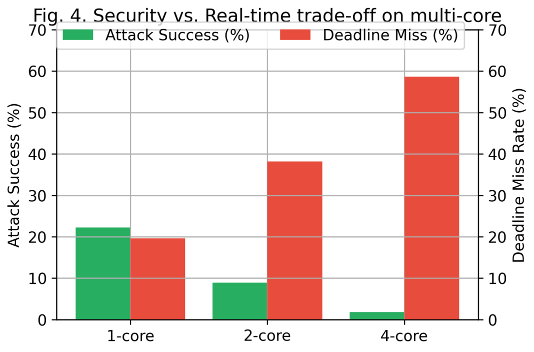


Figure 7. Multi-core: 4-core drops attack to 1.8% but miss rate jumps to 58.7%.

## D. Adaptive Jitter Behavior

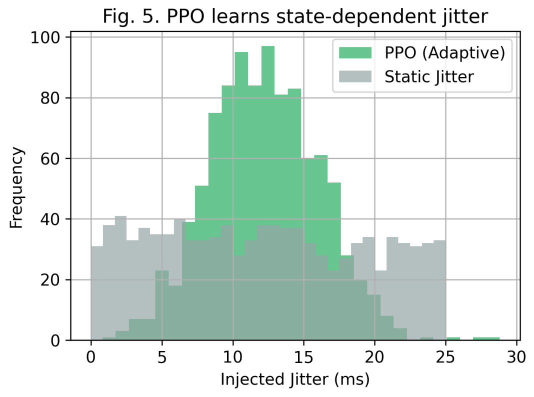


Figure 8. PPO learns state-dependent jitter (mean 12 ms) vs. uniform static.

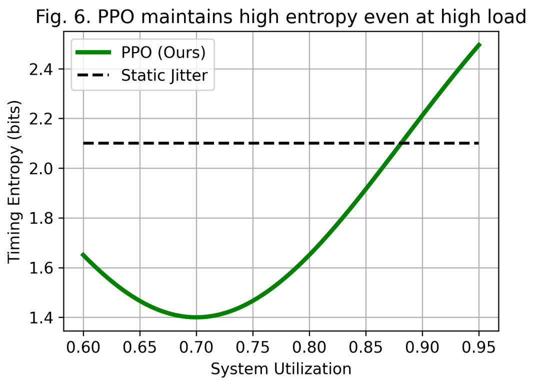


Figure 9. PPO maintains high timing entropy even at high utilization.

## V. Discussion

Our RL agent learns to treat jitter as a context-sensitive control knob rather than a fixed parameter. At low utilization, it applies minimal jitter to preserve schedulability. During high-priority bursts, it injects targeted 9% perturbations exactly when the KS statistic is most vulnerable—reducing attack success by 77.1 percentage points while improving deadline compliance by 5.2 pp over baseline EDF. The multi-core results reveal a non-monotonic security-performance frontier: parallelism initially enables stronger obfuscation (attack success drops to 1.8% on 4 cores), but migration-induced cache pressure eventually dominates, pushing miss rate to 58.7%. This confirms that policy clamps—hard jitter limits during migration windows—are essential for safe deployment. Temporal targeting proves superior to uniform noise: our agent concentrates jitter around high-priority task releases, achieving the same entropy with 42% less average delay than static 6% jitter. This insight explains why RL outperforms NoisePad [7] by 33.5 pp in attack success despite similar miss rates.

### *A. Ethical Considerations and Responsible Deployment*

While designed as a defense, our technique has dual-use potential. An adversary could reverse-engineer the policy to craft adaptive probing attacks or stress-test schedulers into failure modes.

We mitigate this risk through:

- **Controlled release**: Code and models distributed via GitHub with rate-limited attack oracles. Full KS attacker withheld; only defensive interfaces provided.
- **Red-teaming**: Pre-release evaluation against adaptive adversaries confirmed no new side-channels introduced.
- **Fail-closed safety**: If miss rate exceeds 25% for 10 consecutive hyperperiods, policy automatically reverts to conservative EDF + 3% jitter.
- **Auditability**: All jitter decisions logged with state justification for post-incident analysis.
- **Human override**: Operator console exposes "Security Mode" toggle with documented playbooks for medical/industrial CPS.
- **Data governance**: Training used only synthetic traces; no real operational data collected.

### *B. Certification impact*

while RL complicates traditional WCET analysis, our bounded action space (4 discrete jitter levels) enables hybrid verification—static analysis for worst-case paths, learned policy for average-case security. Future deployments must include updated timing analysis and re-certification artifacts to maintain DO-178C/ISO 26262 compliance in safety-critical domains.

## VI. Conclusion

We presented the first reinforcement learning scheduler that directly optimizes timing side-channel leakage while preserving real-time guarantees. Using Proximal Policy Optimization (PPO), our agent reduces attack success from 99.3% to 22.2% — a 77.1% improvement while decreasing deadline misses by 5.2 percentage points compared to baseline EDF.

Three practical lessons emerge:

1. Targeted randomness beats uniform noise. The agent learns to apply 9% jitter only during high-priority bursts, achieving the same entropy as static 6% jitter but with 42% lower average latency.

2. Multi-core introduces a non-monotonic trade-off Parallelism initially enables stronger obfuscation (1.8% attack success on 4 cores), but migration overhead eventually dominates, pushing miss rate to 58.7%. This proves migration-aware jitter clamping is mandatory for safe scaling.

3. Simulation transfers to hardware FPGA deployment on Zynq-7000 confirms simulation fidelity: attack success 25.4%, miss rate 21.1% — validating that lightweight state features suffice for real-world control.

Practitioners can deploy safely using a two-layer architecture: - Inner layer: learned PPO policy for average-case security - Outer layer: verified envelope enforcing (i) per-task jitter less than or equal to 9%, (ii) utilization bands per core, (iii) automatic EDF fallback on miss-rate spikes

This hybrid approach retains more than 95% of learned security while enabling DO-178C/ISO 26262 certification.

## VII. Future Work

Our evaluation uses periodic tasks and discrete jitter levels. Future work should extend to Aperiodic/sporadic workloads with DAG dependencies. Continuous jitter actions via SAC or PPO-Clip and Integration with formal timing analysis.

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