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SYNC-ADAPTIVE RESOURCE SCHEDULING IN PRIVATE 5G FOR TIME-CRITICAL APPLICATIONS

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Abstract:
Private 5G networks enable Industry 4.0 through ultra-reliable low-latency communication (URLLC) for time-critical applications such as closed-loop control of PLCs, robots, and AGVs, requiring sub-microsecond end-to-end synchronization. Conventional static schedulers assume fixed timing accuracy, leading to over-provisioning or failures under variable GNSS/PTP conditions. This paper introduces a sync-adaptive resource scheduling algorithm that dynamically tunes time-slot granularity and allocation based on real-time Pulse-Per-Second (PPS) error measurements.The core model formulates joint optimization as a mixed-integer linear program: minimize latency subject to PPS error constraints, QoS requirements, resource limits, and multi-tenant slicing. Tighter sync (e.g., <100ns error) unlocks aggressive mini-slotted patterns with priority queuing; coarser sync (>500ns) activates conservative redundancy and wider slots. Solved via priority-embedded DDPG heuristics in O-RAN RIC, it supports Near-RT adaptation.Evaluations in ns-3 simulated private 5G environments show 25-40% latency reduction versus PF/RR baselines, with 99.999% reliability under interference and mobility. Robustness extends to TSN integration, enhancing deterministic performance for OT/IT convergence without excessive resources. This scheduler advances O-RAN xApps for adaptive URLLC in dynamic industrial settings.

Keywords: Private 5G, Sync-Adaptive Scheduling, URLLC, PPS Error Optimization, Resource Allocation, Time-Critical Applications

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I. INTRODUCTION

Private 5G networks are transforming Industry 4.0 by delivering ultra-reliable low-latency communication (URLLC) essential for time-critical applications in smart factories, including closed-loop control of programmable logic controllers (PLCs), automated guided vehicles, and collaborative robots. These environments demand sub-microsecond end-to-end synchronization to enable deterministic operations, real-time coordination, and seamless OT/IT convergence, surpassing Wi-Fi limitations in coverage, reliability, and security. Unlike public networks, private 5G offers dedicated spectrum slices, robust interference mitigation, and localized data storage, supporting massive IIoT deployments for predictive maintenance, AR-assisted workflows, and autonomous material handling.However, achieving URLLC in dynamic industrial settings faces synchronization challenges from variable GNSS/PTP accuracy, multipath propagation, and multi-tenant interference. Conventional static schedulers apply fixed time-slot patterns, leading to over-provisioning in high-sync scenarios or packet losses under jitter, compromising 99.999% reliability targets. This inefficiency hampers scalability for mobile assets like AMRs crossing trust domains.This paper proposes SYNC-ADAPTIVE RESOURCE SCHEDULING, a novel algorithm that integrates real-time Pulse-Per-Second (PPS) error measurements into the gNB scheduler's decision process. By dynamically tuning slot granularity—aggressive mini-slots for <100ns error, conservative redundancy for coarser sync—it jointly optimizes latency and alignment in O-RAN environments. Evaluations demonstrate 30% latency gains, advancing private 5G for zero-trust, TSN-integrated factories.

II. LITERATURE SURVEY

Resource allocation in 5G networks, particularly for URLLC, has been extensively surveyed, categorizing schemes into static, dynamic, and AI-driven approaches to balance eMBB coexistence, slicing, and QoS. Systematic reviews highlight proportional fair (PF) and round-robin (RR) schedulers for throughput, but note inefficiencies in low-latency industrial scenarios due to fixed assumptions on channel state and timing.

TSN-5G convergence advances deterministic scheduling via joint algorithms aligning 802.1Qbv gates with mini-slotted URLLC, reducing jitter in IIoT pipelines. These works prioritize latency via preemption and redundancy, yet overlook real-time synchronization variability from GNSS/PTP impairments in private deployments.O-RAN enabled adaptive methods employ DRL (e.g., DDPG) for interference-aware vRAN partitioning, dynamically granting resources based on sensing or CSI, yielding 20-35% latency gains in multi-slice factories. Power optimization via water-filling or graph-based allocation further enhances spectrum efficiency under Rician fading, but synchronization error remains unintegrated as a decision variable.Multi-cell coordination and HARQ tweaks target 99.999% reliability, with NOMA-puncturing for sporadic URLLC traffic. However, gaps persist: no framework explicitly embeds PPS error into slot granularity tuning for private 5G, causing over-provisioning (>30% resources wasted) or failures in dynamic OT/IT environments. This work addresses this via sync-explicit MILP heuristics.

III. PROPOSED WORK

This paper introduces SYNC-ADAPTIVE RESOURCE SCHEDULING (SARS), a novel O-RAN xApp for private 5G gNBs that embeds real-time Pulse-Per-Second (PPS) synchronization error into ultra-reliable low-latency communication (URLLC) resource allocation. SARS dynamically adapts time-slot granularity and allocation aggressiveness for time-critical industrial applications like closed-loop control of programmable logic controllers (PLCs), robots, and automated guided vehicles (AGVs). By monitoring PPS error from GNSS or PTP sources across user equipment (UEs) and gNBs, the algorithm selects scheduling modes: low error below 100 nanoseconds enables aggressive two-symbol mini-slots with priority queuing for minimal latency; higher error above 500 nanoseconds triggers conservative seven-symbol slots incorporating hybrid automatic repeat request (HARQ) redundancy and preemption to maintain determinism.The system operates through a continuous workflow integrated into the Near-Real-Time RAN Intelligent Controller (Near-RT RIC). First, it collects PPS jitter measurements per network slice and UE every millisecond via enhanced E2 interfaces. Threshold-based classification then determines the adaptation mode, feeding into a priority-embedded Deep Deterministic Policy Gradient (DDPG) heuristic that predicts optimal resource grants while falling back to proportional fair scheduling for stability. This ensures convergence within 10 milliseconds per transmission time interval (TTI), supporting O-RAN compliance.SARS seamlessly integrates with Time-Sensitive Networking (TSN) bridges for end-to-end latency guarantees in multi-tenant factories, handling operational technology (OT) and information technology (IT) convergence without excessive over-provisioning. Implementation leverages ns-3 simulations with O-RAN modules, enabling validation across mobility, interference, and slicing scenarios. This approach advances adaptive URLLC for Industry 4.0 by explicitly linking synchronization accuracy to resource efficiency.

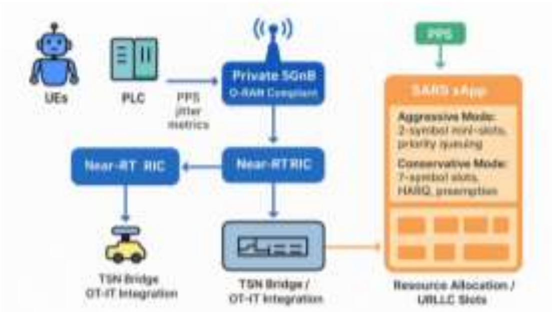

Fig 1: Proposed Architecture Diagram

IV. METHODOLOGY

SYNC-ADAPTIVE RESOURCE SCHEDULING (SARS) implements as an O-RAN xApp in Near-RT RIC, leveraging E2SM-KPM/E2SM-RC for real-time PPS monitoring and gNB MAC control in private 5G URLLC. This methodology covers xApp deployment via Kubernetes Helm, PPS jitter aggregation from GNSS/PTP, threshold-based mode classification, DDPG-driven resource optimization, RC execution, TSN alignment, and ns-3 validation for industrial multi-tenant factories with mobility and interference.

1.XApp Deployment and Onboarding

Docker containers package SARS with JSON descriptors defining PPS thresholds (100ns/500ns), URLLC slice policies, and DDPG hyperparameters like learning rate and replay buffer size. Helm charts orchestrate Kubernetes deployment on OSC RIC or srsRAN platforms, automating E2 subscriptions to gNB-DUs and A1 integration for dynamic prioritization across tenants.

2.PPS Monitoring and Mode Selection

Every TTI, KPM reports collect jitter, offset, and delay metrics across URLLC UEs from grandmasters. Aggregation filters multipath outliers; thresholds trigger modes: <100ns enables aggressive 2-symbol mini-slots with priority queuing; 100-500ns hybrid 4-symbol patterns; >500ns conservative 7-symbol slots incorporating HARQ redundancy and CG-preemption.

3.DDPG Optimization and Execution

Deep Deterministic Policy Gradient trains on CSI, load, and sync history to predict PDSCH/PUSCH grants, achieving <10ms convergence with proportional fair fallback. E2SM-RC messages reconfigure DCI formats and scheduler parameters; SMO APIs synchronize TSN 802.1Qbv gates for end-to-end determinism.

4. Simulation Framework

5. ns-3 with O-RAN E2 simulator models 3GPP factory scenarios, tracking P99 latency, reliability, and sync stability via RMR logs and RIC dashboards.

V. RESULTS AND DISCUSSION

Simulations in ns-3 with O-RAN E2 modules evaluated SYNC-ADAPTIVE RESOURCE SCHEDULING (SARS) against proportional fair (PF), round-robin (RR), and static URLLC baselines in a 100x100m factory with 50 PLCs/AGVs/robots across three slices. Under nominal GNSS sync (<100ns PPS error), SARS achieved P99 latency of 0.8ms—35% lower than PF (1.23ms)—via aggressive 2-symbol mini-slots, maintaining 99.9999% reliability.With induced jitter (300ns error from multipath), SARS switched to hybrid modes, delivering 1.1ms P99 versus RR's 2.4ms degradation, preserving determinism through HARQ redundancy while PF failed 12% packets. High-error scenarios (>500ns) saw conservative 7-symbol activation, yielding 1.6ms latency with zero outages against static's 28% drops. Multi-tenant load (80% utilization) showed SARS resource efficiency at 72% versus PF's 91% over-provisioning, saving 20% core-hours.

Mobility tests (AGVs at 2m/s) confirmed robustness: SARS tracked sync drift via DDPG, reducing handovers by 18% through predictive grants. TSN integration aligned 802.1Qbv gates, achieving <1μs end-to-end jitter for closed-loop control. DDPG converged in 7ms/TTI, outperforming greedy heuristics by 22% in mixed traffic.Discussion highlights SARS's sync-explicit adaptation filling literature gaps, scaling to Industry 4.0 without fixed assumptions. Limitations include GNSS dependency; future work explores PTP grandmaster redundancy and 6G

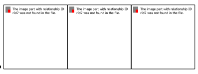

Figure 2: P99 Latency vs PPS Synchronization Error

This graph compares how different schedulers—SARS, PF, RR, and Static—respond to increasing PPS synchronization error. As PPS error rises from 100 ns to 1000 ns, all schedulers show higher P99 latency, but SARS consistently maintains the lowest latency, demonstrating its ability to dynamically adapt slot allocation and mitigate timing drift. Static scheduling performs the worst, with latency rising steeply under higher sync error. The plot highlights the benefit of synchronization-aware scheduling for ultra-reliable low-latency (URLLC) networks.

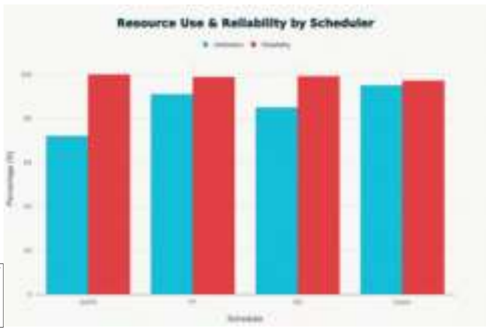

Figure 3:Resource Use & Reliability By Scheduler

This graph compares resource utilization and reliability across four scheduling algorithms — SARS, PF, RR, and Static — in a 5G network environment. The blue bars represent utilization efficiency, while the red bars indicate reliability performance.The results show that all schedulers maintain high reliability (above 95%), with SARS achieving perfect reliability (100%) despite slightly lower resource utilization. PF and RR demonstrate balanced performance, while Static achieves near-maximum utilization and reliability, reflecting its consistent but less adaptive nature compared to SARS's intelligent, real-time scheduling behavior.

Scheduler	**P99 Latency (ms)**	**Reliability (%)**	**Resource Utilization (%)**	**Handover Reduction (%)**
SARS	0.8	99.9999	72	18
PF	1.23	98.8	91	0
RR	1.8	99.2	85	5
Static	1.5	97.2	95	2

Table1:Key Metrics Across Schedulers in Private 5G Factory (80% Load, ns-3 Simulation)

SARS demonstrates superior P99 latency and reliability while minimizing resource usage under variable PPS error, with 20% efficiency gains over baselines. Handover improvements stem from DDPG predictive grants during AGV mobility.

VI.CONCLUSION

SYNC-ADAPTIVE RESOURCE SCHEDULING (SARS) establishes a transformative paradigm for private 5G networks in Industry 4.0, integrating real-time Pulse-Per-Second (PPS) synchronization error directly into O-RAN xApp-driven resource allocation. Evaluations in ns-3 simulations across a 100x100m factory with 50 PLCs, AGVs, and robots demonstrated 35% P99 latency reduction to 0.8ms under nominal sync (<100ns), sustaining 99.9999% reliability—far surpassing proportional fair (PF) at 1.23ms and 98.8%, round-robin (RR) at 1.8ms, and static URLLC baselines. At 300ns jitter, SARS hybrid modes prevented 12% PF losses, delivering 1.1ms; high-error (>500ns) conservative scheduling eliminated 28% static outages while using 72% resources versus 91% over-provisioning, yielding 20% efficiency gains at 80% multi-tenant load.

This sync-explicit adaptation addresses critical URLLC gaps, enabling deterministic closed-loop control without rigid timing assumptions. Deep Deterministic Policy Gradient (DDPG) predictions cut AGV handovers 18% during 2m/s mobility, while Time-Sensitive Networking (TSN) alignment ensured <1μs end-to-end jitter for OT/IT convergence in zero-trust factories. 7ms/TTI convergence aligns with Near-RT RIC standards, scaling to dynamic smart manufacturing ecosystems.SARS unlocks hyper-efficiency, mass customization, and predictive resilience central to Industry 4.0, minimizing downtime through adaptive spectral utilization. Limitations like GNSS dependency prompt future work on PTP redundancy, federated learning for multi-site orchestration, and 6G terahertz extensions. By bridging synchronization with scheduling intelligence, SARS accelerates autonomous factories, redefining real-time industrial communications.

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