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Agentic Cross-Layer Mobility Management for Reliable 6G IoT Networks

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***Abstract*—Future 6G IoT smart environments will comprise large populations of mobile cyber-physical entities operating under stringent reliability and latency requirements. Unlike traditional static IoT deployments, mobility becomes an intrinsic system property that continuously alters network topology, communication quality, and resource availability. Consequently, maintaining reliable and deterministic communication requires the coordinated adaptation of localization, routing, handover, and scheduling mechanisms. However, existing mobility-management approaches remain largely reactive and typically optimize these functions independently, limiting their ability to support mobility-intensive industrial environments.**

This paper presents an Agentic Mobility Management for 6G IoT networks (AMM-6GIoT), which is a hierarchical agentic cross-layer orchestration framework for deterministic IoT communication systems. The proposed architecture jointly coordinates mobility perception, cooperative localization, proactive handover, routing adaptation, and mobility-aware TSCH scheduling across mobile, edge, and cloud layers. Unlike conventional reactive solutions, AMM-6GIoT formulates mobility support as a coupled orchestration problem spanning multiple communication layers and temporal scales. A representative industrial smart-environment use case is further discussed to illustrate the orchestration challenges of future mobility-intensive IoT systems.

***Index Terms*—6G IoT, mobility management, smart environments, TSCH, edge intelligence, federated learning, proactive handover**

I. Introduction

Future industrial IoT systems operating in 6G environments will involve large numbers of mobile devices, such as robots, automated guided vehicles (AGVs), and wearable systems, interacting in highly dynamic and time-critical settings. In such environments, maintaining reliable and low-latency communication is not merely a performance objective, but a strict requirement for safe and efficient operation of cyber-physical processes. Mobility is no longer an exceptional event; it is a normal operating condition that continuously alters topology, link quality, interference, traffic demand, and resource availability.

However, current mobility-management mechanisms are still largely reactive, initiating handovers only after link degradation has already been detected. This reactive behavior, combined with frequent topology changes and high device density, leads to unstable connectivity, increased packet loss, ping-pong handovers, control overhead, and service interruption. As a result, existing wireless and IoT systems struggle to provide predictable and time-sensitive communication under dynamic mobility conditions.

Recent advances in 6G communication, edge intelligence, and deterministic wireless networking further intensify the need for integrated mobility-aware orchestration architectures. Emerging industrial IoT deployments increasingly rely on mobile cyber-physical systems interacting through low-power wireless infrastructure under stringent reliability and latency constraints [1]. At the same time, deterministic scheduling frameworks such as IEEE 802.15.4e TSCH and 6TiSCH continue to experience significant performance degradation under topology changes and mobile communication conditions [2]. Recent work on edge-assisted orchestration, multi-agent AI, and MEC coordination also demonstrates the growing importance of hierarchical decision-making across device, edge, and cloud layers [3], [4].

A fundamental limitation is that mobility management and communication scheduling are treated as independent problems. Mobility mechanisms focus on maintaining connectivity through handover decisions, while scheduling mechanisms, particularly in time-sensitive IoT systems, are designed under the assumption of relatively stable network conditions. Consequently, mobility-induced changes invalidate scheduling decisions, leading to degraded end-to-end performance. This decoupled design prevents current systems from achieving reliable and predictable operation in highly dynamic environments.

This limitation is further reflected in the trade-off between distributed and centralized mobility-management approaches, illustrated in Figure 1. Distributed mechanisms provide fast local responsiveness but rely on limited context, often resulting in unstable and suboptimal decisions. Centralized approaches leverage global network knowledge to improve coordination, but introduce significant signaling overhead and scalability limitations under dense mobility conditions. This trade-off highlights the absence of a unified approach capable of achieving responsiveness, coordination, and scalability at the same time.

Addressing this challenge requires a shift from reactive and decoupled mechanisms toward coordinated and predictive control across system layers. Mobility decisions and communication scheduling must be jointly optimized based on real-time context and system-wide coordination. This motivates a distributed, multi-agent approach capable of integrating perception, localization, handover decision-making, and scheduling

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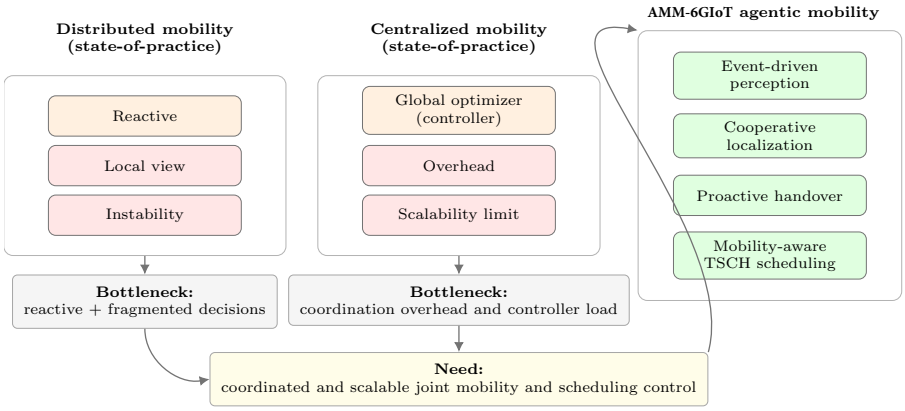


Fig. 1. Motivation for agentic mobility management: the limitations of distributed and centralized mobility control highlight the need for coordinated, scalable, and joint mobility–scheduling control in 6G IoT smart environments.

into a unified control architecture.

This paper argues that reliable mobility support in 6G IoT smart environments should be formulated as a *hierarchical multi-agent cross-layer orchestration problem*. Instead of designing handover, routing, localization, and scheduling as separate mechanisms, the system should coordinate decision-making across mobile devices, edge infrastructure, and cloud learning components. The goal is not merely to augment conventional mobility management with AI, but to establish a closed-loop orchestration framework in which mobility context, communication resources, and network control decisions are continuously coordinated to maintain reliable and deterministic operation under dynamic mobility conditions.

II. Related Work and Technical Gap

Research on mobility management for 5G and emerging 6G systems has advanced along several interconnected directions, including cellular mobility procedures, edge-assisted control, distributed learning, and MAC-layer scheduling for low-power IoT [1], [5]–[7]. These developments motivate a shift toward more autonomous, predictive, and coordinated mobility management architectures.

Recent standardization efforts, particularly within 3GPP Release 16, introduced Conditional Handover (CHO), which separates preparation and execution to improve robustness in time-varying radio conditions. CHO has demonstrated reductions in handover failures and has been extended to non-terrestrial networks [8]. Despite these improvements, most mobility control in 5G systems remains reactive, making it sensitive to user density and high mobility. Contemporary surveys emphasize that future mobility mechanisms must become predictive, energy-aware, and more resilient to network dynamics [1]. Complementary work on next-cell prediction using deep learning models within O-RAN controllers shows improved accuracy and reduced retraining time through transfer learning [9]. Reinforcement learning (RL) has also been used to jointly optimize handover parameters, revealing trade-offs among radio-link failures, latency, and signaling overhead; these methods often rely on digital twins to reduce the risks of online experimentation [10].

In parallel, mobility management in low-power IoT networks has followed a separate evolution. Network-based approaches such as PMIPv6, HMIPv6, and hierarchical mobility extensions reduce the burden on constrained devices but incur considerable signaling overhead, especially when mobility is frequent or the topology is large [11]. RPL-based approaches such as mRPL [12] and mRPL+ [13] improve responsiveness through mobility-aware routing adaptation. However, their decisions remain primarily local, which limits their ability to maintain stable behavior in dense and dynamic environments. With the emergence of software-defined networking (SDN), IoT mobility solutions such as SDMob [5] have shown that global network views can improve packet delivery and reduce delay, although controller bottlenecks persist in dense deployments. These limitations suggest that neither fully centralized nor fully distributed approaches are sufficient for dense 6G IoT deployments.

Edge computing has become a key enabler in overcoming some of these bottlenecks. Mobile edge computing (MEC)-based mobility architectures can reduce reaction time and improve handover preparation, while coordination with SDN facilitates more consistent network-wide decision-making [3], [4]. Nevertheless, current MEC systems rarely integrate mobility-aware deterministic wireless scheduling with distributed learning. As a result, they often support service orchestration without fully addressing how mobility affects the underlying low-power wireless communication substrate.

Distributed intelligence is also emerging as a promising direction. Federated learning (FL) enables collaborative model training across heterogeneous mobile or IoT devices without centralizing data. Recent work on federated meta-learning for indoor localization demonstrates rapid adaptation to new deployment environments with limited calibration effort [14]. Broader surveys confirm the relevance of FL for bandwidth-limited and privacy-sensitive IoT networks [15]. Concurrently, advances in indoor localization across Wi-Fi, BLE, UWB, and IMU sensors highlight localization as a key requirement for future 6G systems, with an increasing focus on sensor fusion and ML-based fingerprinting [16].

Agentic AI has recently emerged as a defining component of

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envisioned 6G architectures. Studies propose using lightweight autonomous agents, such as TinyML models deployed on the edge, to support proactive mobility actions and context-preserving intent handover between nodes [17]. The 6G strategic roadmaps emphasize that autonomous agents capable of reasoning will underpin IMT-2030 networks, enabling semantic-level coordination and self-optimizing network functions [18]. These perspectives align with a broader trend toward hierarchical and multi-agent decision-making.

Despite these advances, mobility remains unresolved for low-power industrial IoT networks at the MAC layer. In 6TiSCH, the Minimal Scheduling Function (MSF) provides basic mechanisms for slot negotiation and schedule updates, but adapts poorly to rapid topology changes, often resulting in schedule churn and inconsistent slot allocation [2]. Cross-layer enhancements that integrate RPL control messages with scheduling decisions can reduce joining delay and overhead, yet still lack explicit mobility-awareness [7]. More broadly, deterministic communication mechanisms span two largely disconnected domains: TSN-enabled 5G systems, which rely on centralized and infrastructure-dependent scheduling, and TSCH-based IoT networks, which offer lightweight and distributed wireless scheduling. Both paradigms typically assume relatively stable conditions and therefore do not provide a complete solution for dynamic mobility.

Rather than summarizing this landscape as a table, the core gap can be stated as four design tensions. First, prediction improves handover preparation, but does not automatically repair deterministic schedules. Second, edge coordination improves visibility, but can become a bottleneck under dense mobility. Third, distributed intelligence protects privacy and responsiveness, but suffers under partial observability. Fourth, TSCH scheduling provides deterministic behavior but is not inherently mobility-aware. The missing element is a unified architecture that jointly coordinates mobility detection, localization, handover, and scheduling across heterogeneous time scales.

III. Agentic AMM-6GIoT Architecture

AMM-6GIoT addresses this gap by introducing a multi-agent mobility-management model in which multiple cooperating agents jointly perform perception, localization, proactive handover planning, and resource management across mobile devices, edge infrastructure, and a cloud learning layer. As illustrated in Figure 2, the proposed system forms a closed-loop control architecture in which distributed agents perform mobility perception and prediction, cooperative localization, proactive handover planning, and mobility-aware TSCH scheduling.

The architecture has three interacting layers. The mobile layer performs event-driven detection and short-term mobility prediction. These local agents monitor link-quality variation, mobility indicators, packet statistics, and context changes. Their role is to generate timely mobility events without relying on periodic signaling or late link-failure triggers.

The edge layer performs fast-loop coordination. It hosts localization and context agents, a handover orchestrator, a TSCH agent, and a coordination agent for policy alignment. This layer is responsible for translating mobility events into proactive handover plans and schedule adaptations. Because it operates closer to the devices than the cloud, it can support millisecond to sub-second adaptation while still maintaining a broader view than individual nodes.

The cloud layer performs slower-loop learning and global policy refinement. It aggregates historical information, supports model updates, and provides long-term adaptation. This layer is suitable for reinforcement learning, digital-twin-assisted training, and cross-site policy transfer, but should not be responsible for every fast mobility decision.

The key design principle is hierarchical separation of time scales. Local mobile agents handle immediate events, edge agents coordinate fast network responses, and cloud agents refine policies over longer horizons. This separation avoids the brittleness of fully distributed decisions and the scalability limitations of fully centralized control.

IV. Multi-Agent Cross-Layer Mobility Orchestration

The proposed AMM-6G architecture formulates mobility management as a hierarchical multi-agent orchestration problem rather than as isolated routing, handover, localization, or scheduling tasks. This perspective is motivated by recent work on predictive handover, edge-assisted orchestration, and mobility-aware deterministic communication, where mobility, queue evolution, routing consistency, and schedule adaptation are increasingly recognized as tightly coupled control variables rather than independent protocol functions [1], [2], [5].

Let

$$\mathcal{N} = \{n_1, n_2, \ldots, n_K\}$$

denote the set of mobile IoT nodes and

$$\mathcal{E} = \{e_1, e_2, \ldots, e_M\}$$

the set of edge orchestration agents. Each mobile node $n_i \in \mathcal{N}$ continuously observes its local mobility and communication state:

$$x_i(t) = [p_i(t), v_i(t), l_i(t), b_i(t), q_i(t), \rho_i(t)]$$

where:

- $p_i(t)$ denotes the estimated position of node n_i,
- $v_i(t)$ denotes the velocity vector,
- $l_i(t)$ represents wireless link-quality indicators such as RSSI, packet reception ratio, and delay,
- $b_i(t)$ denotes neighboring beacon observations used for cooperative localization,
- $q_i(t)$ represents queue occupancy and traffic demand,
- and $\rho_i(t)$ denotes the current routing and parent-selection state.

These variables directly correspond to the main orchestration functions of AMM-6G, namely mobility perception, localization refinement, routing adaptation, proactive handover, and mobility-aware TSCH scheduling.

For each edge agent $e \in \mathcal{E}$, let $\mathcal{N}_e(t) \subseteq \mathcal{N}$ denote the set of mobile nodes currently associated with that edge controller. The regional orchestration state is therefore defined as:

$$X_e(t) = \{x_i(t) \mid n_i \in \mathcal{N}_e(t)\}.$$

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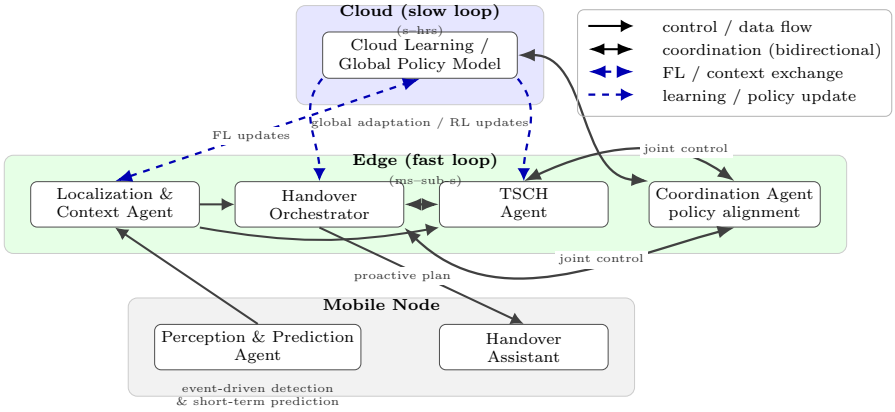


Fig. 2. AMM-6GIoT architecture: a coordinated multi-agent mobility management, supporting TSCH scheduling across mobile, edge, and cloud layers.

Unlike centralized SDN approaches that continuously collect complete network state information, the proposed architecture only exchanges context required for proactive orchestration decisions. This reduces signaling overhead while preserving sufficient visibility for mobility coordination [5].

Using the regional orchestration state, the edge layer predicts short-term mobility evolution:

$$\hat{p}_i(t+\Delta t) = f_m\left(p_i(t), v_i(t), b_i(t), \mathcal{H}_i(t)\right),$$

where $f_m(\cdot)$ denotes the mobility-prediction function and $\mathcal{H}_i(t)$ denotes historical mobility observations for node n_i. The prediction horizon Δt should match the timescale of handover preparation and schedule adaptation. A short prediction horizon improves accuracy but reduces orchestration time, whereas a longer horizon improves planning capability while increasing uncertainty.

Based on predicted mobility and communication conditions, the edge agent selects a coordinated orchestration action:

$$u_e(t) = \left[u_e^{ho}(t), u_e^{loc}(t), u_e^{rt}(t), u_e^{sch}(t)\right],$$

where:

- $u_e^{ho}(t)$ denotes proactive handover coordination,
- $u_e^{loc}(t)$ denotes cooperative localization refinement,
- $u_e^{rt}(t)$ denotes routing or parent-selection adaptation,
- and $u_e^{sch}(t)$ denotes TSCH schedule adaptation.

The ordering of these operations is important because localization and mobility prediction influence handover preparation, while handover and routing changes directly affect TSCH schedule validity and synchronization consistency.

For a mobile node n_i, let $\mathcal{A}_i(t)$ denote the set of candidate attachment points or parent nodes. The proactive handover decision is formulated as:

$$u_i^{ho}(t) = \arg\max_{a\in\mathcal{A}_i(t)} \Big[w_1\hat{R}_{i,a}(t+\Delta t) - w_2\hat{D}_{i,a}(t+\Delta t) - w_3\hat{S}_{i,a}(t+\Delta t) - w_4 C_{i,a}^{ho}(t)\Big]$$

where:

- $\hat{R}_{i,a}(t+\Delta t)$ denotes predicted link reliability,
- $\hat{D}_{i,a}(t+\Delta t)$ denotes predicted communication delay,
- $\hat{S}_{i,a}(t+\Delta t)$ denotes predicted TSCH scheduling instability,
- and $C_{i,a}^{ho}(t)$ denotes handover cost.

The weighting coefficients $w_1, \ldots, w_4$ represent application-specific priorities. For example, industrial control systems may prioritize reliability and schedule consistency, whereas battery-constrained sensing applications may prioritize lower signaling overhead and energy efficiency.

This formulation differs from conventional signal-strength-based handover mechanisms. In deterministic IoT networks, the strongest link is not necessarily the optimal attachment point because schedule instability and synchronization disruption may significantly affect end-to-end reliability.

TSCH schedule adaptation is triggered when predicted mobility conditions are likely to violate communication requirements. A simple adaptation condition may be expressed as:

$$\hat{P}_i^{loss}(t+\Delta t) > \theta_{loss} \quad \text{or} \quad \hat{S}_i(t+\Delta t) > \theta_{sch},$$

where $\hat{P}_i^{loss}(t+\Delta t)$ denotes predicted packet-loss probability, $\hat{S}_i(t+\Delta t)$ denotes predicted scheduling instability, and θ_{loss} and θ_{sch} are orchestration thresholds. This enables proactive adaptation before mobility-induced degradation becomes visible as packet loss or synchronization failure.

The global orchestration objective is to minimize mobility-induced communication degradation over a planning horizon T:

$$\min_{\{u_e(t)\}_{t=0}^{T}} \sum_{t=0}^{T} \left[\alpha D(t) + \beta H_f(t) + \gamma S_u(t) + \delta O(t) + \zeta U(t)\right],$$

where:

- $D(t)$ denotes communication disruption,
- $H_f(t)$ denotes handover failure cost,
- $S_u(t)$ denotes scheduling-update instability,
- $O(t)$ denotes orchestration overhead,
- and $U(t)$ denotes localization uncertainty.

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The optimization objective is subject to practical IoT constraints:

$$E_i(t) \leq E_i^{max}, \quad O_e(t) \leq O_e^{max}, \quad D_i(t) \leq D_i^{max},$$

where $E_i(t)$ denotes energy consumption for node n_i, $O_e(t)$ denotes orchestration overhead at edge agent e, and $D_i(t)$ denotes communication delay. These constraints are important because proactive orchestration should improve mobility robustness without overwhelming constrained devices or edge infrastructure with excessive signaling or scheduling updates.

The cloud layer operates at a slower temporal scale and performs policy refinement rather than direct real-time orchestration. Using historical mobility traces and communication observations, orchestration parameters are updated as:

$$\Theta(t+1) = g\left(\Theta(t), \mathcal{D}_{hist}\right),$$

where Θ denotes orchestration parameters such as mobility-prediction models, handover thresholds, and scheduling policies, while $\mathcal{D}_{hist}$ denotes historical mobility and communication data. This hierarchical separation between fast edge decisions and slower cloud optimization improves scalability while preserving sufficient adaptability for mobility-intensive environments.

The proposed AMM-6G framework therefore combines:

- mobility perception and short-term movement prediction,
- cooperative localization,
- proactive handover coordination,
- routing adaptation,
- and mobility-aware TSCH scheduling

within a unified orchestration architecture. The central idea is that these functions should not be optimized independently because handover decisions affect routing stability, routing changes affect queue dynamics, queue evolution affects TSCH cell demand, and schedule changes influence delay, reliability, synchronization stability, and energy consumption.

V. Industrial Smart-Environment Use Case and System Implications

Figure 3 illustrates a representative industrial smart-environment scenario based on the proposed AMM-6GIoT architecture. The environment includes autonomous mobile robots, AGVs, wearable devices, industrial sensors, distributed edge infrastructure, and deterministic wireless communication systems operating simultaneously under mobility-intensive industrial conditions.

Figure 4 illustrates the architectural tradeoff motivating AMM-6GIoT. Distributed mobility mechanisms introduce low coordination overhead but rely on limited local visibility, which can lead to fragmented decisions under dense mobility. Centralized orchestration provides broader coordination but its signaling and controller load increase rapidly as mobility density grows. AMM-6GIoT aims to occupy the middle ground by distributing decisions across mobile, edge, and cloud layers, thereby improving coordination without requiring continuous global-state collection.

The use case demonstrates why mobility management in future 6G IoT systems should not be treated as an isolated handover problem. Mobile robots continuously move across wireless coverage regions while exchanging traffic with heterogeneous latency and reliability requirements. AGVs transporting industrial materials require predictable control communication, wearable devices support worker monitoring and safety, and distributed sensors continuously report operational information.

In such environments, mobility affects not only radio connectivity, but the entire communication and orchestration pipeline. A mobile node approaching a new coverage region may simultaneously require localization refinement, parent reselection, handover preparation, TSCH schedule adaptation, synchronization recovery, and queue stabilization. If these functions operate independently, the network may preserve basic connectivity while still violating deterministic timing requirements and application deadlines.

This challenge becomes particularly important in TSCH-based deterministic wireless systems. Traditional TSCH scheduling mechanisms assume relatively stable neighborhood relationships and slowly varying traffic conditions. Under mobility-intensive industrial environments, however, valid communication links, interference conditions, and queue dynamics continuously evolve. Consequently, mobility-induced topology changes may invalidate scheduling assumptions, increase synchronization instability, and trigger excessive schedule adaptation.

The use case also highlights the limitations of purely distributed approaches. Local reactive decisions may provide fast adaptation, but often suffer from fragmented visibility and suboptimal coordination. A node may select the strongest available parent without considering scheduling instability, synchronization cost, or future mobility direction. Conversely, fully centralized orchestration improves global visibility, but introduces controller bottlenecks and signaling overhead under dense mobility conditions.

The central idea of AMM-6GIoT is therefore that mobility prediction, localization, handover coordination, routing adaptation, and deterministic scheduling should be jointly coordinated because these functions are strongly interdependent. A handover changes routing state; routing changes affect queue dynamics; and queue evolution modifies TSCH scheduling demand and synchronization stability.

Future evaluation should therefore move beyond conventional packet-delivery metrics and additionally consider handover interruption time, synchronization recovery delay, TSCH schedule churn, orchestration overhead, localization uncertainty, deadline misses, and resilience under dense mobility conditions.

VI. Conclusion

This paper presented AMM-6GIoT, a hierarchical agentic cross-layer orchestration framework for mobility-aware deterministic communication in future 6G IoT smart environments. Unlike conventional reactive mobility mechanisms, AMM-6GIoT jointly coordinates mobility prediction, proactive handover, cooperative localization, routing adaptation, and TSCH scheduling across mobile, edge, and cloud layers. The paper argued that reliable mobility support in future industrial IoT systems should be treated as a coupled orchestration problem

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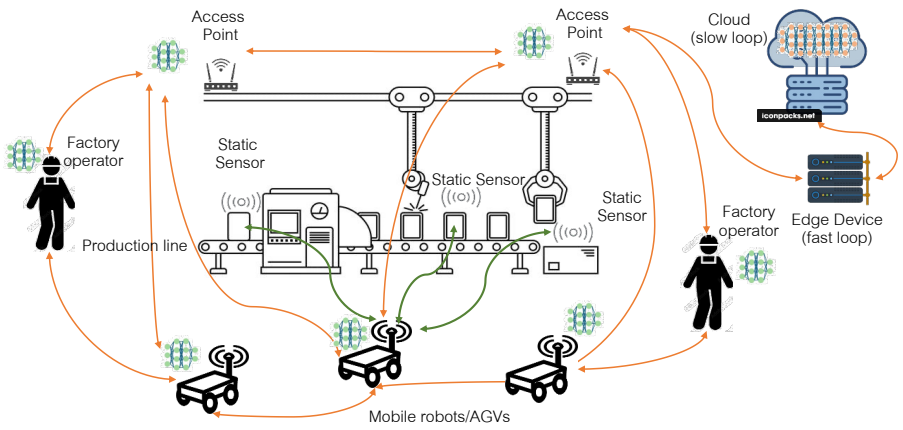


Fig. 3. Representative industrial smart-environment use case involving mobile robots, industrial IoT devices, edge orchestration, and mobility-aware deterministic wireless communication.

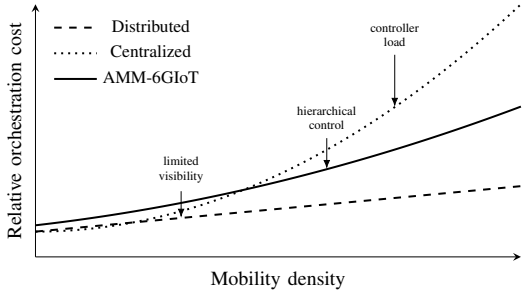


Fig. 4. Conceptual scalability tradeoff among distributed, centralized, and AMM-6GIoT mobility orchestration. The curves are illustrative, not measured results.

rather than an isolated networking function. Future work will focus on reinforcement-learning-based orchestration, digital-twin-assisted optimization, and experimental validation under realistic industrial mobility conditions.

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