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Guest Editorial

Collaborative Embodied Artificial Intelligence for Industrial Internet of Things Networks

The Industrial Internet of Things is evolving from a collection of connected sensors and machines into an operational environment populated by autonomous robots, mobile platforms, intelligent controllers and human operators. In this setting, intelligence is not confined to data centres or isolated devices. It is embodied in physical agents that perceive their surroundings, exchange information, make decisions and act upon industrial processes. Collaboration among these agents is becoming essential in manufacturing, logistics, energy systems, process industries, construction and infrastructure inspection.

Embodied artificial intelligence brings perception, reasoning and control into direct interaction with the physical world. An embodied agent must interpret multimodal observations, respond to uncertain conditions and complete tasks under strict safety and timing requirements. Its decisions depend not only on the quality of its local models, but also on the availability of communication, computing and sensing resources. This dependence is particularly important in industrial environments, where wireless channels may be obstructed by machinery and structures, computing capacity differs across devices and operational conditions can change rapidly.

Collaboration extends the capabilities of individual agents. Robots can share observations to improve environmental awareness, coordinate trajectories to avoid conflicts and divide complex missions according to their capabilities. Fixed sensors, edge servers and digital twins can provide additional context for planning and control. Human operators can also contribute supervision, domain knowledge and intervention when automated decisions become uncertain. Such cooperation enables industrial systems to operate with greater flexibility and resilience, but it introduces close dependencies among communication, computation, perception and control.

Conventional Industrial Internet of Things architectures often treat these functions separately. Communication protocols are commonly designed to maximise throughput or minimise latency, while learning and control methods assume that information is available with sufficient accuracy and timeliness. These assumptions become difficult to sustain when several embodied agents share limited spectrum and computing resources. A delayed observation, an incomplete model update or an unreliable control message can directly affect physical operation. Network design must therefore account for the operational value of information rather than relying only on conventional measures of traffic volume and link quality.

Collaborative embodied intelligence requires communication mechanisms that reflect task context. Not every observation has equal importance, and the value of a message may change as a mission progresses. An alert concerning an unsafe machine state should receive different treatment from a routine visual update. Likewise, transmitting complete sensor streams may be unnecessary when compact features, semantic representations or task specific summaries are sufficient for coordination. Task aware communication can reduce network load while preserving the information needed for reliable decisions.

Edge computing provides an important foundation for this transition. By placing computation close to machines and robots, industrial systems can reduce response times, limit dependence on remote infrastructure and retain sensitive operational data within controlled environments. However, edge resources are finite and unevenly distributed. Effective operation requires decisions about where perception, inference, planning and model updates should be executed. These decisions must consider communication conditions, device energy, processing delay, task urgency and the consequences of failure. Joint management of networking and computing resources is therefore central to scalable collaborative embodied systems.

Learning across multiple agents raises further questions. Centralised training can exploit broad operational data, whereas decentralised execution allows agents to act without continuous access to a central controller. Federated and distributed learning can support knowledge exchange while limiting the transfer of raw industrial data. Graph based models can represent changing relationships among robots, machines and infrastructure. Multi agent reinforcement learning can support role assignment, resource allocation and coordinated control. Nevertheless, these methods must contend with partial observability, nonstationary behaviour, limited training data and the difficulty of verifying policies before physical deployment.

Digital twins can complement embodied agents by providing virtual representations of equipment, processes and operating environments. They can support policy training, system testing, fault diagnosis and predictive maintenance without exposing physical assets to unnecessary risk. Their effectiveness depends on consistent synchronisation between virtual and physical systems. This creates demanding requirements for data freshness, model fidelity and communication reliability. Integrating digital twins with edge intelligence and collaborative control remains an important research direction for Industrial Internet of Things networks.

Safety, security and trust are equally fundamental. Collaborative agents may exchange sensor observations, learned representations, control intentions and model parameters. Adversarial manipulation or accidental corruption of this information can propagate through the system and affect physical processes. Appropriate safeguards are needed for authentication, access control, anomaly detection, privacy protection and resilient decision making. Industrial operators must also be able to understand why an agent selected a particular action, especially when decisions affect workers, equipment or production continuity. Explainability and human oversight should consequently be treated as system requirements rather than optional additions.

This Special Issue examines the networking, computing and intelligence foundations required for collaborative embodied artificial intelligence in Industrial Internet of Things environments. Its contributions address topics such as distributed perception, semantic and task aware communication, edge intelligence, multi agent coordination, digital twin integration, resource management, robot networking, safe control and trustworthy learning. Together, they show that reliable embodied collaboration cannot be achieved by improving a learning model or communication link in isolation. Progress requires designs that connect network performance with perception quality, decision accuracy and physical task outcomes.

The studies presented in this Special Issue also highlight several open problems. Industrial deployments need methods that remain effective across different devices, radio environments and task configurations. Collaborative policies must scale to larger groups without excessive signalling or training costs. Models trained in simulation must transfer reliably to physical systems. Communication and computing decisions should adapt to changing task value while maintaining predictable performance. Evaluation methods must extend beyond average accuracy and throughput to include safety, robustness, energy use, recovery from failure and the completion of industrial tasks.

Standardisation and reproducible experimentation will be important for translating current research into practice. Shared benchmarks should represent realistic industrial channels, heterogeneous hardware, multimodal sensing and physical constraints. Experimental reports should describe network assumptions, computing platforms, task definitions and failure conditions in sufficient detail to permit comparison. Open datasets, simulation environments and reference implementations can help researchers assess whether improvements remain valid outside narrowly defined scenarios. At the same time, collaboration with industrial users is needed to ensure that proposed solutions address operational requirements, regulatory obligations and integration costs.

We hope that this Special Issue provides readers with a clear account of recent progress and remaining challenges in collaborative embodied intelligence for Industrial Internet of Things networks. The field sits at the intersection of communications, networking, machine learning, robotics and control. Its development will depend on sustained cooperation across these communities and on careful validation in representative industrial environments.

We thank all authors for submitting their work and responding constructively to the review process. We are also grateful to the reviewers for their careful assessments and valuable recommendations. Finally, we thank the editorial team of IEEE Internet of Things Magazine for its guidance and support throughout the preparation of this Special Issue.