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Self-Evolving Distributed AI for Adaptive IoT Ecosystems

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Abstract

Intelligence in Internet of Things (IoT) ecosystems is largely centralized and limited in its capacity to adapt, learn new tasks quickly, and optimize its operation. EdgeMind offers a framework for self-evolving distributed intelligence, enabling a high level of autonomy for intelligent applications. Each application can be decomposed into dedicated components along the edges of the cloud-edge continuum, acting on local data and collaborating with others for coordination and knowledge sharing. A diverse range of learning and adaptation mechanisms is supported to address these tasks and drive continual improvement of intelligent components. More broadly, EdgeMind provides an operational architecture to support intelligence at multiple levels of autonomy; the focus here is on applications that require a significant level of independence.

A meta-architectural approach is adopted, allowing independent design and development of components. Novelty is embedded within the module-specific learning loops that enable EdgeMind to meet the intelligence-oriented research directions set forth in recent reports by the UK Government Office for Science, AI Council and Defence and Security Accelerator. The design welcomes adaptation and optimization of operation (including the profile of computation and communication resources) through self-optimization, continual learning and meta-learning. EdgeMind is therefore positioned to go beyond established paradigms such as federated learning by addressing the learning and adaptation needs of applications across the full diversity of the AI/ML lifecycle and operational continuum.

Keywords : Edge AI,Distributed Intelligence,Internet of Things (IoT),Self-Evolving Systems,Autonomous Learning,Edge Computing,AIoT (Artificial Intelligence of Things),Federated Learning,Multi-Agent Systems,Adaptive Intelligence,Decentralized AI,Real-Time Analytics,Resource-Constrained Environments,Intelligent Edge Devices,Collaborative Edge Intelligence.

1. Introduction

Data-driven intelligence in the Internet of Things (IoT) ecosystem is typically implemented using centralized Artificial Intelligence (AI) embedded into the service provider cloud. Addressing the key challenge of evolving expectations regarding the provision of local services with an appropriate level of trust and resilience requires complementing these systems with distributed intelligence at the edge. Distributed Intelligence enables localized provisioning of services, has a different failure model than centralized AI, and avoids orchestrated malicious behaviour. However, it lacks autonomous, self-evolution capabilities. This redefinition of its nature enables, for example, sharing environment knowledge gained during the lifetime of deployed instances and developing new models for tasks similar to the ones already resolved, using limited labelled data — key features for a technology that operates under zero trust assumptions, with strong resource constraints.

Although various techniques focused on self-evolving intelligence exist (e.g., Federated Learning and Continual Learning), the underlying architecture does not support their combined adoption in IoT edge environments. The EdgeMind framework integrates AI in practical deployment scenarios as a new form of Self-Evolving Distributed Intelligence, accommodating this need. It employs Learning Loop principles for intuitive representability of Federated Learning, Continual Learning, and Meta-Learning, and aligning these techniques with Resource-Aware System objectives. Prior research provided an initial validation of the design, and a concrete real-world deployment showcased the framework operationalization. Further literature review and research are now needed to establish comprehensive metrics and evaluation processes for intelligence, adaptability, and efficiency in Distributed Intelligence.

1.1. Background and Significance

Complex, interconnected systems operating on a massive scale and requiring functional resilience are ubiquitous in nature and society. While such systems display surprising levels of coordination, they generally rely on neither a common control model nor a centralized planning agent. Each individual contributes to the overall system through relatively simple self-centered behavior, yet the global behavior emerges progressively as a by-product of individual interactions. Such a form of collective intelligence endows the system with problem-solving capabilities that are beyond the individual capabilities of its constituents. These manifestations of intelligence, adapted to the needs and constraints of the organizational building blocks, correspond to examples of distributed intelligence.

Intelligence is among the attributes that remain underexplored in the context of massive-scale IoT ecosystems. Furthermore, the potential for AI systems to evolve through interaction within the ecosystem has only recently received attention. It is this aspect of collective intelligence that EdgeMind seeks to foster—collective intelligence in the form of distributed intelligence exhibiting self-evolution capabilities in an unintrusive manner. Such an approach fits naturally in the context of the Internet of Things, where multiple physical and virtual agents interact to achieve common objectives. Indeed, most positions on artificial general intelligence seem to acknowledge that distributed intelligence is a more plausible form of general intelligence than singularity. In addition, distributed intelligence is a natural fit with the Edge Computing paradigm.

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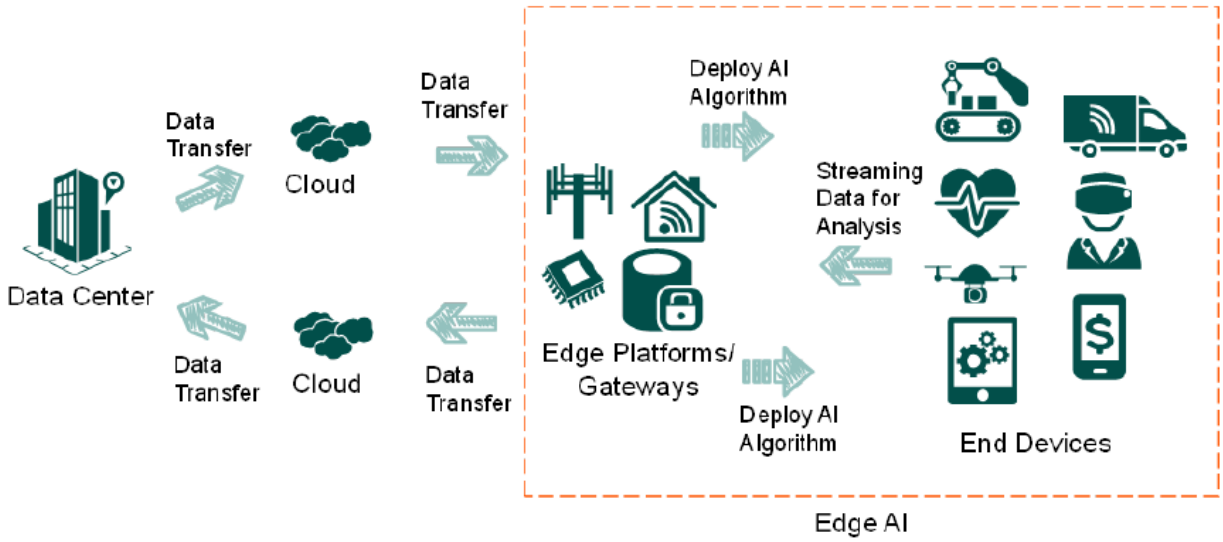

Fig 1: Building an Edge AI Ecosystem

1.2. Research design

The overarching goal is to define a framework that enables practical self-evolving distributed intelligence in IoT ecosystems. The practical utility of such a framework is assessed by establishing evaluation criteria and testing in diverse representative scenarios. The framework's suitability for application development and integration with existing facilities is also evaluated.

Prior research exploring variants of distributed intelligence—intelligence dispensed and shared across devices rather than centralized within a cloud—is reviewed to lay a theoretical foundation that unifies a broad range of approaches, including self-optimizing methods. A collaborative self-evolving architecture is proposed for dynamic and cooperative networks of connected devices in the IoT space. Intelligence is instilled in End-Systems and Artifacts, deep learning in Edge-Services. JoN, a Publish/Subscribe standard messaging system and the central Data & Work Governance component, constitute the foundation for development. Evaluation addresses the adaptation and intelligence qualities of Dynamic-Federated Learning; a unit-based optimization framework for self-optimizing devices; a meta-learning approach harnessing Memory-Augmented Neural networks for fast adaptation to new tasks; and a resource-aware partitioning of adaptation functions that accounts for computation, communication, and energy constraints. An Industrial-IoT deployment built on the framework serves as a case study.

Equation 1: Local learning objective at each EdgeMind agent

Let agent $i$have local dataset

$$D_i = \{(x_{ij}, y_{ij})\}_{j=1}^{n_i}$$

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and local model parameters

$$w_i \in \mathbb{R}^d$$

If the loss on one sample is $\ell(w_i; x_{ij}, y_{ij})$, then the average local loss is

$$F_i(w_i) = \frac{1}{n_i} \sum_{j=1}^{n_i} \ell(w_i; x_{ij}, y_{ij})$$

Step-by-step derivation

For one sample:

$$\text{sample loss} = \ell(w_i; x_{ij}, y_{ij})$$

For all $n_i$samples:

$$\sum_{j=1}^{n_i} \ell(w_i; x_{ij}, y_{ij})$$

Average per sample:

$$\frac{1}{n_i} \sum_{j=1}^{n_i} \ell(w_i; x_{ij}, y_{ij})$$

So the local training objective is

$$\boxed{F_i(w_i) = \frac{1}{n_i} \sum_{j=1}^{n_i} \ell(w_i; x_{ij}, y_{ij})}$$

2. Theoretical Foundations

Distributed Intelligence

The concept of distributed intelligence encompasses systems endowed with degrees or elements of intelligence and the coordination of their tasks distributed among these intelligent agents, subsystem, or element to achieve a common aim. Intelligent

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decisions at distributed elements are usually considered separate, but still, those decisions need coordination and collaboration to make the desired result better than operating only by those intelligent agents acting alone. Those distributed contributions may perform into a supervised or unsupervised way or under a combination of both perspectives. Central to the concept of distributed intelligence is the assumption that learning agents, rather than numerical model outputs, are collected, transferred, and employed by participants in outcomes.

Previous work in the area of distributed intelligence for the Internet of Things (IoT) proposed a multi-agent concept for Artificial Intelligence in the IoT in which IoT components generate small learning agents that share, aggregate, and improve distributed learning models. In the IoT context and especially when dealing with edge-computing resources, intelligence is not generated in a central point but rather is scattered through the system. Thus, utilization of a distributed paradigm when considering intelligence able to act, react, adapt, and learn with the environment is recommended both under a real-time point of view and in terms of hardware resource utilization and energy consumption. In these cases, the combination of Distributed Intelligence, Cooperative Multi-Agent Systems and Learning appears to be the best solution. Models of Distributed Intelligence integrated with model-based coordination mechanisms are especially appropriate for structured classification systems that require simple and rapid decisions, for allocation problems, and for systems whose performance does not heavily depend on the homogeneity of the communication network.

Module	Function	Key Responsibilities
Perception	Data acquisition	Collects data from sensors and peer agents
Reasoning	Knowledge generation	Interprets data and produces insights
Learning	Model improvement	Uses federated + continual learning
Control	Resource management	Manages compute, energy, communication
Governance	Trust & safety	Ensures privacy, security, compliance

Table 1: EdgeMind Core Modules

2.1. Distributed Intelligence

Distributed Intelligence represents a specific manifestation of distributed systems performing intensive systems that require

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extreme levels of cooperation. Distributed intelligence is not merely a collective of intelligent agents, nor is it simply an organized super entity. A distributed intelligence is composed of different agents with roles, social structure, and coordination mechanisms to produce intelligent behaviour. Unlike centralized intelligence that typically relies on precise, very reliable communication, distributed intelligence is not fragile to partial messages, unreliable channels or communication delays. The normal operation of distributed intelligent systems allows for agents temporarily disconnecting or failing to produce some of their results without interrupting the system, and yet by working together, these systems can sustain and support much higher loads than the sum of their independent capacities. They also provide more qualitative results than the application of centralized intelligence models. The systems based on Distributed Intelligence achieve these benefits without relying on redundancy, but through the re-allocation and specialisation of the system capacities determined by social roles. Although they need to be designed and calibrated to such a large number of factors, the Principle of Organized Emergence of Distributed Intelligent Systems offers an efficient approach for doing so.

The very motivation underlying the distributed intelligence development of a distributed intelligence lies in its decentralised and self-organised nature. Distributed intelligent systems tend to face a vast number of unstructured interrelated problems with data and parameters that may change with time. For most applications in AI, these are environments where, given the lack of global organisation, coordination of the system operation is inefficient and expensive compared to a bottom-to-top organised one where the agents themselves discover which tasks can be performed together to obtain the best results.

The core motivation behind the development of distributed intelligence lies in its decentralized and self-organizing nature, which allows systems to operate effectively without relying on a central authority. Such systems are particularly suited to complex, dynamic environments where numerous unstructured and interrelated problems arise, and where data and parameters continuously evolve over time. In traditional centralized approaches, coordinating system operations can be inefficient, costly, and often impractical due to the lack of global visibility and control. In contrast, distributed intelligent systems adopt a bottom-up approach, enabling individual agents to interact, adapt, and collaboratively determine optimal task groupings. Through this self-coordination, agents can respond more flexibly to changes, improve scalability, and achieve more efficient problem-solving outcomes, making distributed intelligence a powerful paradigm for modern AI applications.

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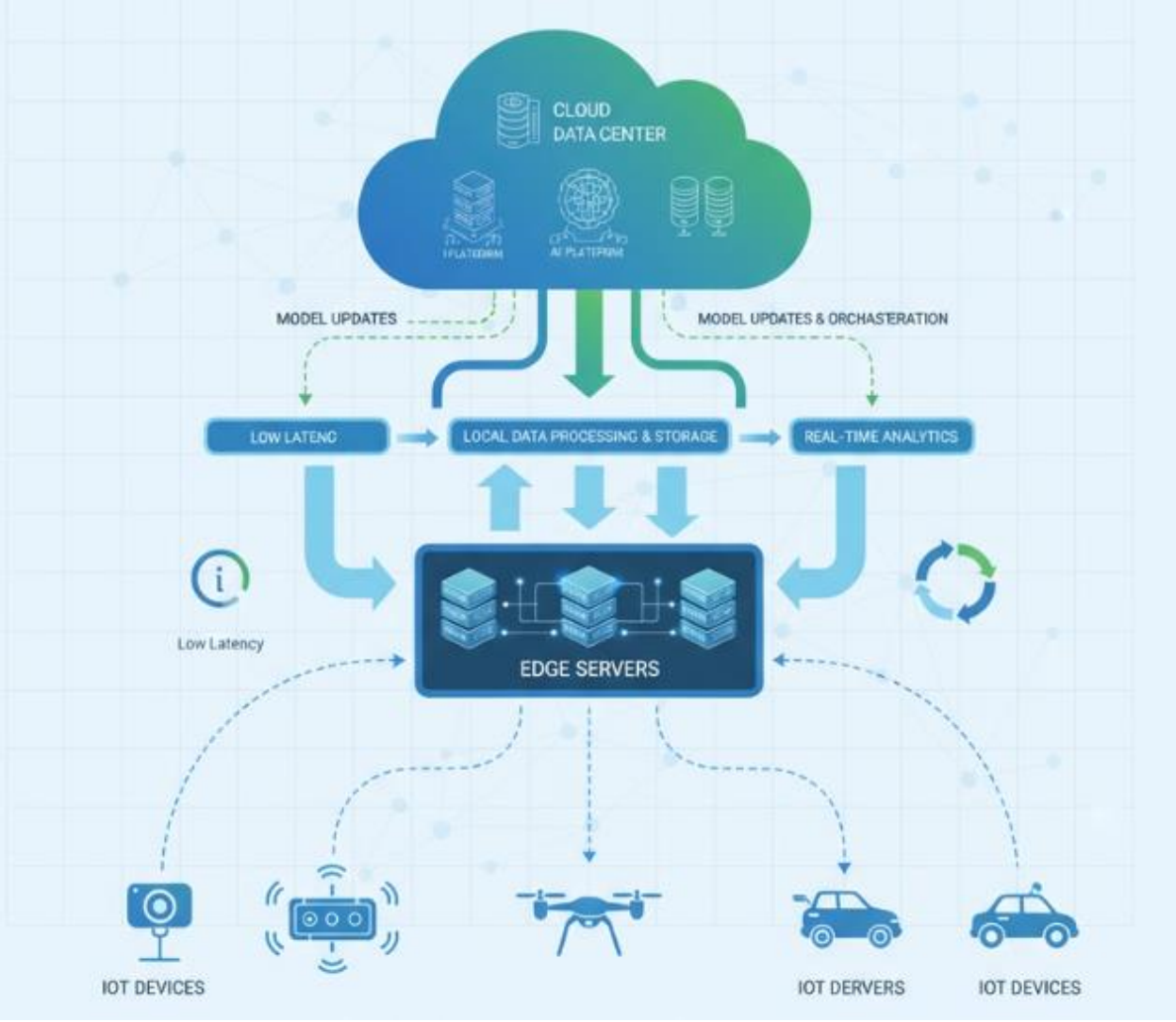

Fig 2: Edge Computing The Complete Technical Guide to Distributed Intelligence

2.2. Self-Evolution in AI Systems

The key to achieving distributed intelligence is to enable AI agents to improve their perception, reasoning, learning, adaptation, and governance skills over time. Therefore, these systems should mimic biological systems' capability to learn from their actions, new environments, and evolving tasks by representing experiences as models (policies, rules, and classifiers); adapting to

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changes in input distributions and learning new tasks without forgetting previously acquired skills; and optimizing resource consumption. Self-evolving systems need the ability to perform continual and federated learning and approaches using meta-learning techniques.

Continual Learning Continual learning seeks to model performance in terms of an agent's ability to learn and adapt to a new environment while retaining the knowledge necessary to preserve overall performance. State-of-the-art methods for continual learning employ various techniques to avoid overfitting or forgetting prior tasks, combine the knowledge learned from prior tasks with new information, and focus on learning relevant tasks while suppressing irrelevant ones. In accordance with the definition of distributed intelligence, continual learning in EdgeMind follows a federated learning paradigm. Agents collaborate to build and share global models that capture common structures and variations across environments while adapting and personalizing them to their local contexts.

Equation 2: Global federated aggregation (FedAvg-style)

Let total data across participating agents be

$$N = \sum_{i=1}^{K} n_i$$

If each client finishes a local update and returns $w_i^{(t+1)}$ at round $t+1$, then the global model is the data-weighted average:

$$w^{(t+1)} = \sum_{i=1}^{K} \frac{n_i}{N} w_i^{(t+1)}$$

Step-by-step derivation

Each client should influence the global model in proportion to how much data it owns.

Weight of client i:

$$\alpha_i = \frac{n_i}{N}$$

Since

$$N = \sum_{i=1}^{K} n_i$$

we get

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$$\sum_{i=1}^{K} \alpha_i = \sum_{i=1}^{K} \frac{n_i}{N} = \frac{1}{N} \sum_{i=1}^{K} n_i = 1$$

So a valid weighted average is

$$w^{(t+1)} = \sum_{i=1}^{K} \alpha_i \, w_i^{(t+1)}$$

Substitute $\alpha_i = \frac{n_i}{N}$:

$$\boxed{w^{(t+1)} = \sum_{i=1}^{K} \frac{n_i}{\sum_{m=1}^{K} n_m} \, w_i^{(t+1)}}$$

2.3. IoT Architectures and Edge Compute

Selecting the appropriate computing location for different tasks and applications within an IoT ecosystem has a critical impact on many aspects, including end-user Quality of Experience (QoE), energy consumption, reliability, availability, latency, and response time. A wide range of architectural solutions have been proposed to process large volumes of information from multiple distributed data sources and to manage heterogeneous components, networks, and systems in a scalable and efficient manner. Recent advances in edge computing have given rise to several resource-aware architectural frameworks supporting the edge–cloud continuum. Regardless of their nature, these architectures must take into account the extreme resource constraints typically characterizing IoT devices in order to minimize energy consumption, infrared radiation emission, data delivery time, and risk. Furthermore, given the increasing demand for responsiveness and local processing, many individuals can be expected to reserve a growing part of the cloud data centers.

3. EdgeMind System Architecture

EdgeMind comprises five core modules (perception, reasoning, learning, control, and governance) that facilitate distributed collaboration, self-optimization, and privacy-preserving learning. Perception is responsible for collecting data through local sensors as well as through data streams published by peer agents; the latter capability serves to enable the learning of different aspects of the same phenomenon in parallel, fostering both the accuracy of the agents' models and the knowledge of the community. Reasoning interprets the data and generates knowledge; its operation is assisted by knowledge granularities that improve reasoning efficiency. The learning module employs federated learning principles to alleviate privacy concerns; once skilled, the agents can exploit self-optimization techniques to tune their models without human intervention. Control manages the use of resources (memory, computation, communication, and energy) in accordance with the system's perception of the context, while governance ensures privacy, safety, and trustworthiness at different levels.

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Modules communicate via well-defined interfaces; data flows between them are governed by information-precedence rules that dictate which module can write data to shared memory at any given time. The overall architecture is aligned with the much broader act–observe–learn–decide design pattern, which characterizes intelligent behavior in general, not just in AI systems. The first-order absence of a centralized component is a distinctive feature that reduces the risk of a common point of failure. Data ownership and sharing follow the principles of privacy by design. Data collected by local sensors are owned by the hosting agent, and other agents can rely on published data only if prior consent has been granted; data usage is also limited by the principle of minimization. Furthermore, operators of privacy-sensitive applications can rely on data anonymization or on compliance with Europe's General Data Protection Regulation or similar frameworks.

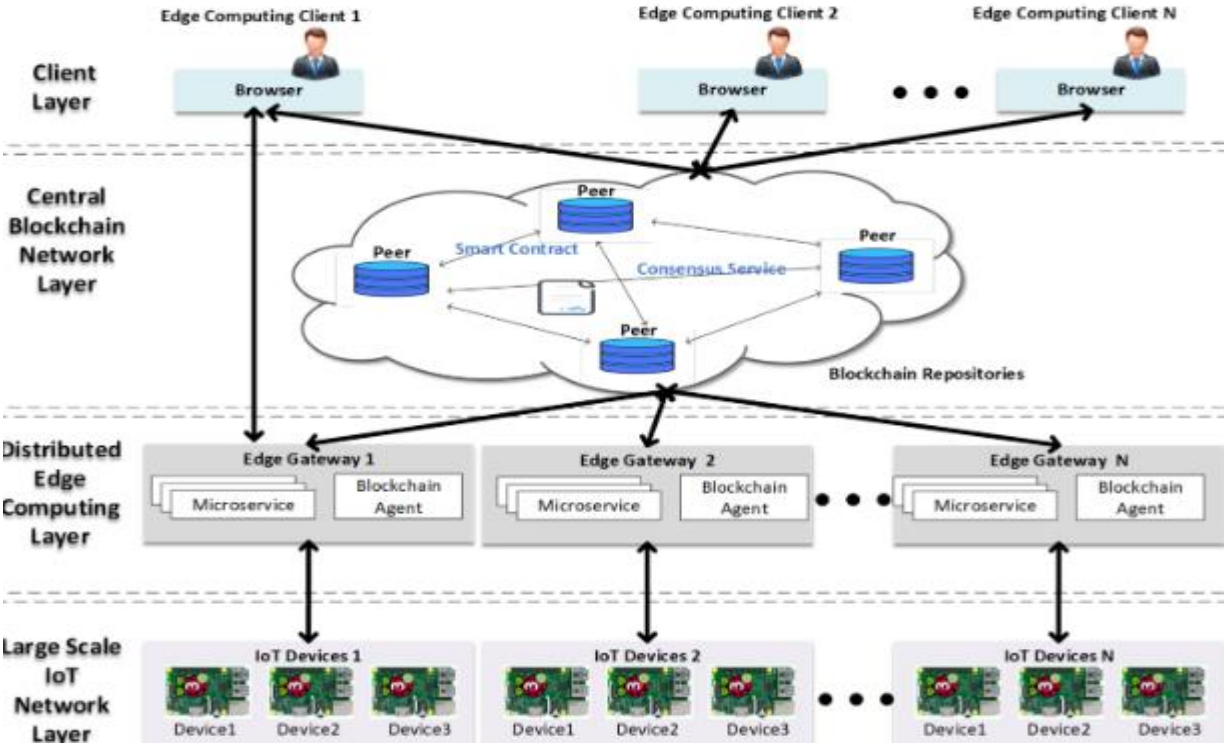

Fig 3: Distributed Secure Edge Computing Architecture

3.1. Core Components and Modules

The architecture comprises the following core components: perception, reasoning, learning, control, and governance. The perception module, which may be split into dedicated submodules, acts as an interface to the surrounding environment. Multiple interfaces (e.g., sensors or robots) capture local information that cannot otherwise be accessed by external agents, and the perception module is responsible for processing the received data. Processed or aggregated data are then made available for

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messaging to other modules through the reasoning module, which implements the system's reasoning capabilities. New types of logical services can be introduced through the addition of reasoning submodules. Since reasoning may be resource-intensive, processed results are made accessible to the learning module, which continuously learns from the results of the reasoning and control modules. Such a learning mechanism can be defined as continual learning. The outputs of the reasoning and learning modules can also be used to autonomously tune or optimize system parameters through the control module.

The control module provides interaction with the surrounding environment, either by controlling actuators or sending commands and SLA requirements to other agents. As in the perception module, the control module can be split into submodules serving concrete actuators or type-specific interactions. Typical agents participating in a Distributed Intelligence process must operate in unknown or hostile environments; therefore, an operational governance capability is required to ensure that requests and actions meet safety requirements and are carried out correctly. The governance module is responsible for establishing trust among participating agents, coordinating communication, and keeping local SLAs.

Equation 3: Continual learning objective with forgetting control

Let:

- w= current parameters
- $w^{\star}$= parameters learned from previous tasks
- Ω_k= importance of parameter k
- λ= forgetting penalty weight

Then the continual-learning objective is

$$\mathcal{L}_{CL}(w) = \mathcal{L}_{new}(w) + \lambda \sum_{k} \Omega_k \, (w_k - w_k^{\star})^2$$

Step-by-step derivation

Start with current-task loss only:

$$\mathcal{L}_{new}(w)$$

But this alone may overwrite older knowledge. So add a penalty that keeps important parameters close to their old values.

Deviation of parameter k:

$$w_k - w_k^{\star}$$

Squared deviation:

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$$(w_k - w_k^\star)^2$$

Weight it by importance Ω_k:

$$\Omega_k (w_k - w_k^\star)^2$$

Sum over all parameters:

$$\sum_k \Omega_k \, (w_k - w_k^\star)^2$$

Scale the whole penalty by λ:

$$\lambda \sum_k \Omega_k \, (w_k - w_k^\star)^2$$

Add this to the new-task loss:

$$\boxed{\mathcal{L}_{CL}(w) = \mathcal{L}_{new}(w) + \lambda \sum_k \Omega_k \, (w_k - w_k^\star)^2}$$

3.2. Data Governance and Privacy by Design

In EdgeMind, data generation, ownership, and sharing follow the "you own your data" principle, offering users full control over their data (see Microsoft Azure's Confidential Computing, offloading data processing to the supporter organization of the application) and "privacy by design" principles, such as access control. User-generated data are disclosed and shared only with consent and for the time and purpose agreed upon. The "data-minimization" principle ensures that only the necessary information is shared, while "data-anonymization" enables data sharing even without consent, as sensitive data are removed or concealed. Nevertheless, it is important to share data with the environments of deployments governed by the GDPR, the Family Education Rights and Privacy Act, and the Health Insurance Portability and Accountability Act in the United States, in order to optimize learning and adaptation capabilities.

The learning and adaptation mechanisms explored are designed to mitigate risks caused by untrusted data and model sharing, and to minimize the impact of potentially compromised nodes on the entire ecosystem. Models, predictions, and aggregation functions are bound to local data ownership, allowing data provenance capture and enabling inference, verification, and trustworthiness attestation of learning and adaptation processes. Data-sharing and model-sharing protocols integrate intelligence and privacy. Provenance is a central component of both the data/AI-traffic-control layer and the trust subsystem, monitoring data/AI flow and ensuring digital forensics, enabling the establishment of trust metrics. The technical foundations of these modules extend established concepts from both data provenance and trust management areas.

3.3. Communication Protocols and Interoperability

Communication in IoT systems is a principal obstacle to efficient data exchange. The EdgeMind approach prescribes the usage of open, published standards, yet acknowledges the existence of multiple protocols, procedures, and data formats that hinder the interchangeability of components, non-vendor lock-in, and resource utilization. Designing a completely agnostic communication architecture for every service is impractical. Instead, a communication layer outlines a communication strategy on a per-use-case basis, defining message formats and protocols based on the specific application.

Interoperability and integration issues may also be addressed by adopting ontologies that describe the knowledge domain and mapping them to the supported data models of each device. Finally, task-specific adapters facilitate the translation between heterogeneous data formats at the point of access.

4. Learning and Adaptation Mechanisms

Distributed intelligent systems should be able to learn and adapt continually, integrating new information, modifying models, and extending knowledge autonomously. EdgeMind incorporates three complementary learning paradigms. Federated and continual learning are used for multiple agents working on shared tasks; self-optimization implements auto-tuning for individual components or systems; and resource-aware adaptation adjusts the response to changes in computation, communication, or energy constraints.

Federated learning aggregates model updates from multiple agents in a privacy-preserving manner; continual learning extends federated learning to data streams and non-stationary tasks; and explored techniques accommodate non-IID data and model drift. A distributed and asymmetric implementation allows agents to retain local models and process data autonomously, accelerating inference and reducing latency. Personalization and adaptation enable locally trained models to specialize for specific data distributions, and drift-detection techniques trigger re-learning whenever deemed necessary. Memory-augmented or attention models enable continual assimilation of task-agnostic experience.

Self-optimization exploits meta-learning principles so the system acquires the ability to tune itself, minimizes the need for expert intervention, and adapts rapidly to new tasks. Agents auto-tune their own parameters, while modules capable of learning how to learn prevent failure caused by hyperparameter misconfiguration. Resource-aware adaptation techniques consider computation and communication loads and energy consumption. Computing resource shortages can be mitigated by offloading or requesting assistance, while requests that would overload an agent can be denied to maintain service quality. A control hierarchy schedules actions, dynamically scaling components for efficiency without sacrificing quality.

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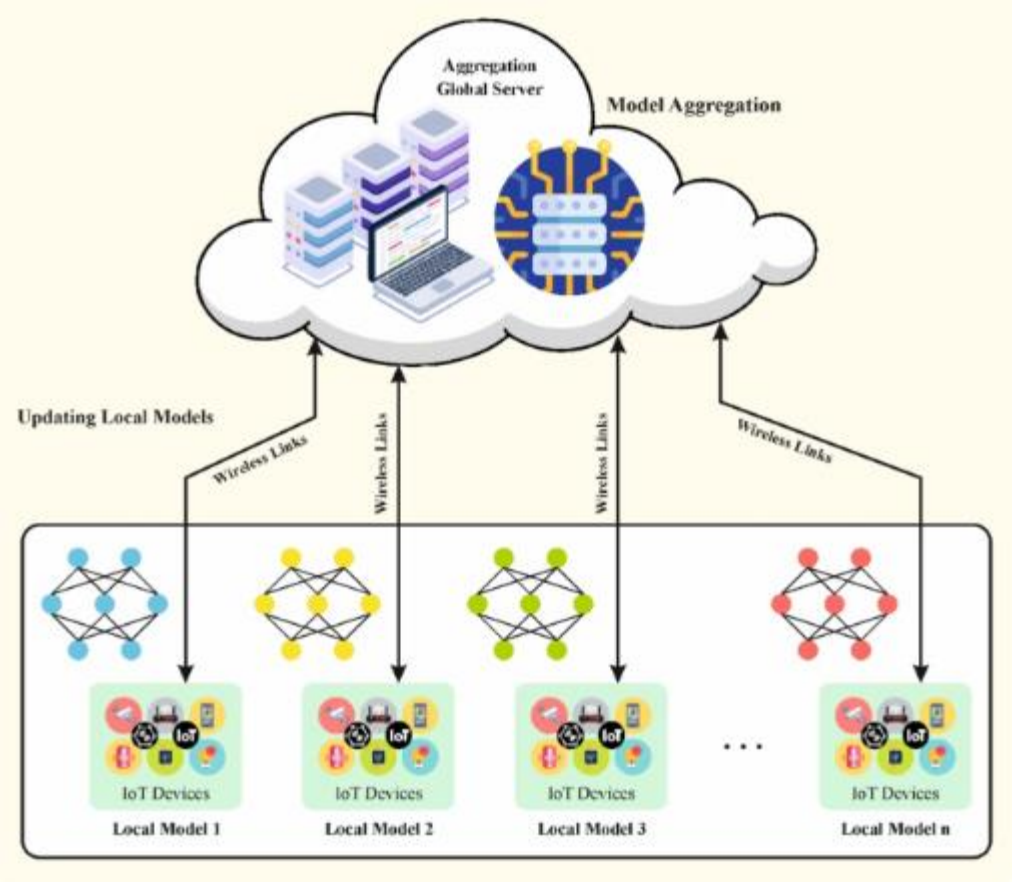

Fig 4: Learning and Adaptation Mechanisms of EdgeMind

4.1. Federated and Continual Learning

Federated Learning (FL) provides a decentralized approach for training a joint model across multiple devices, enabling knowledge sharing and privacy preservation by keeping users' raw data on-device without needing to transfer it to the cloud. FL executes the learning task by exchanging model updates, instead of the original data. Therefore, learning on this kind of non-IID data will bring poor performance due to the different distributions of the data used by various clients. Personalization Learning aims to ameliorate the performance drop by developing personalized models by adding per-client customization to the global model, such as a lightweight adapter. Much of the success of neural networks has been attributed to transfer learning, namely for fine-tuning models pre-trained on a large dataset for downstream tasks with limited data. Moreover, as data is often assumed to be sampled from an ever-changing distribution, different versions of the pre-trained model are required to best adapt to different stages of the distribution. This motivates continual learning — a framework modeling temporal evolution in the data distribution

and addressing problems that arise when models learn from a sequence of tasks, such as forgetting previous tasks and poor initialization when learning new tasks. FL is naturally positioned to optimize distributed training and aggregation of parameters in continual learning.

Apart from these aspects at the model drool mutation side, privacy-preserving proposal has also received much attention. An often applied practice of FL is to share the gradients of the shared model updates instead of the model parameters. This would significantly take less information than parameters, but an attacker can still fully reconstruct the training samples under white-box scenarios. By carefully encrypting the shared updates or applying differential privacy concepts to it, the information leakage can be mitigated while keeping acceptable performance. Finally, the push of advanced devices at the edge often brings more sensors to the system, which can be utilized to provide the privacy-preserving monitoring without disturbing the passive clients.

Mechanism	Description	Purpose
Federated Learning	Shared model updates without raw data	Privacy-preserving collaboration
Continual Learning	Learning from evolving data streams	Avoid forgetting past knowledge
Meta-Learning	Learning how to learn	Fast adaptation to new tasks
Self-Optimization	Auto-tuning system parameters	Reduce human intervention
Resource-Aware Adaptation	Adjusts based on resource limits	Efficient operation

Table 2: Learning & Adaptation Mechanisms

4.2. Self-Optimization and Meta-Learning

The learning mechanism of EdgeMind unifies self-optimization processes and meta-learning in a modular structure. Self-optimization encompasses all components with parameters exposed externally, allowing them to auto-tune ensuing components in the learning and control loops. This mechanism accelerates convergence without requiring explicit control signals and without affecting other key-importance designs, such as privacy. Beneficial combinations for rapid adaptation to new tasks, domains or environments are stored with memory-augmented models allowing them to be selected automatically or through a learning signal. Auto-tuning, memory-augmented models and meta-learning can use different types of available resources.

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Self-optimization measures the suitability of components that can vary—models, aggregators, tuners—and networks for specific situations and optimizes combinations representing distinct capabilities. Usual resource constraints—computation, communication, energy—also affect the data selection, dissemination and scheduling processes, explicitly defined to use available compute resources without incurring unnecessary energy consumption due to communication overhead. These aspects are decisive for Edge AI, deployable anywhere, including IoT contexts where sensors rely on battery energy. Scheduling uses predicted residual battery levels together with links comparing energy savings and prediction accuracy. Scaling strategies, using light-weight models, are applied when computation resources are reduced.

4.3. Resource-Aware Adaptation

Resource constraints are a major consideration for self-evolving, distributed intelligence in IoT ecosystems. The EdgeMind architecture implements strategies to deliver effective performance, within the limits of computation, communication, and energy availability. Three levels of adaptability are supported by the approach: online scheduling and scaling of intelligence modules based on dynamic resource availability (cf. resource allocation); fine-tuning of models during runtime according to changing task specifications, and rapid adaptation to new tasks with reduced training costs.

For each component on the EdgeMind architecture, auto-tuning methods are explored to search for appropriate parameters. Such methods are particularly suited for ML/DL models whose hyper-parameters affect accuracy output. Their applicability across different tasks is typically limited, as reflected by the training costs of domain-adaptive transfer learning that are higher than those of training for the original task. EdgeMind proposes Meta-Reinforcement Learning to achieve rapid adaptation by embedding an external memory with meta-learning. The Memory-Augmented Neural Network (MANN) architecture operating for supervised learning tasks is used as the memory module.

Equation 4: Resource-aware adaptation / Flow-Resource objective

A compact optimization form is:

$$J = \alpha\, L_{task} + \beta\, C_{comp} + \gamma\, C_{comm} + \delta\, E$$

where:

- L_{task}= task loss or error
- C_{comp}= computational cost
- C_{comm}= communication cost
- E= energy consumption
- $\alpha, \beta, \gamma, \delta$= trade-off weights

The agent chooses configuration $a$to minimize:

$$a^{\star} = \arg\min_{a} J(a)$$

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Step-by-step derivation

The paper says EdgeMind must balance:

1. learning quality,
2. computation,
3. communication,
4. energy.

So define a cost for each:

- task error: L_{task}
- compute burden: C_{comp}
- communication burden: C_{comm}
- energy usage: E

Since these quantities are not equally important, assign weights:

$$\alpha, \beta, \gamma, \delta > 0$$

Weighted total objective:

$$J = \alpha L_{task} + \beta C_{comp} + \gamma C_{comm} + \delta E$$

The system then selects the placement/scheduling/model-size decision $a$with minimum total cost:

$$\boxed{a^{\star} = \arg\min_{a} \left[\alpha L_{task}(a) + \beta C_{comp}(a) + \gamma C_{comm}(a) + \delta E(a)\right]}$$

5. Security, Trust, and Safety

Security is integral to trust and safety in complex systems, yet security alone is not sufficient. Trust plays an essential part, supporting mission critical automated services without human oversight. Constitutionally restrictive orders may underpin such automatic trust. Trust is also chainable throughout operating environments, transparently resilient against insider threat and empowering autonomous migration and cooperation, even under intermittently joyful collaboration.

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Safety and reliability are primaries also at design time, ultimately aligning with transparent trust by enabling formally modeled and proven risk profiles for trusted-connected agents before deployment. Mission critical services execute these profiles, monitored in deployment through additional contracts and log studies. Whether agent migrations are safe for the next hop is thus decidable before execution, creating several automated safety levels that ensure normally safe yet seldom guarded operations are, in extreme circumstances, fail-safe and non-disruptive. All safety guarantees must, however, apply at runtime: failure of any advanced check must roll back to a less-relaxed state or abort mission-critical tasks entirely.

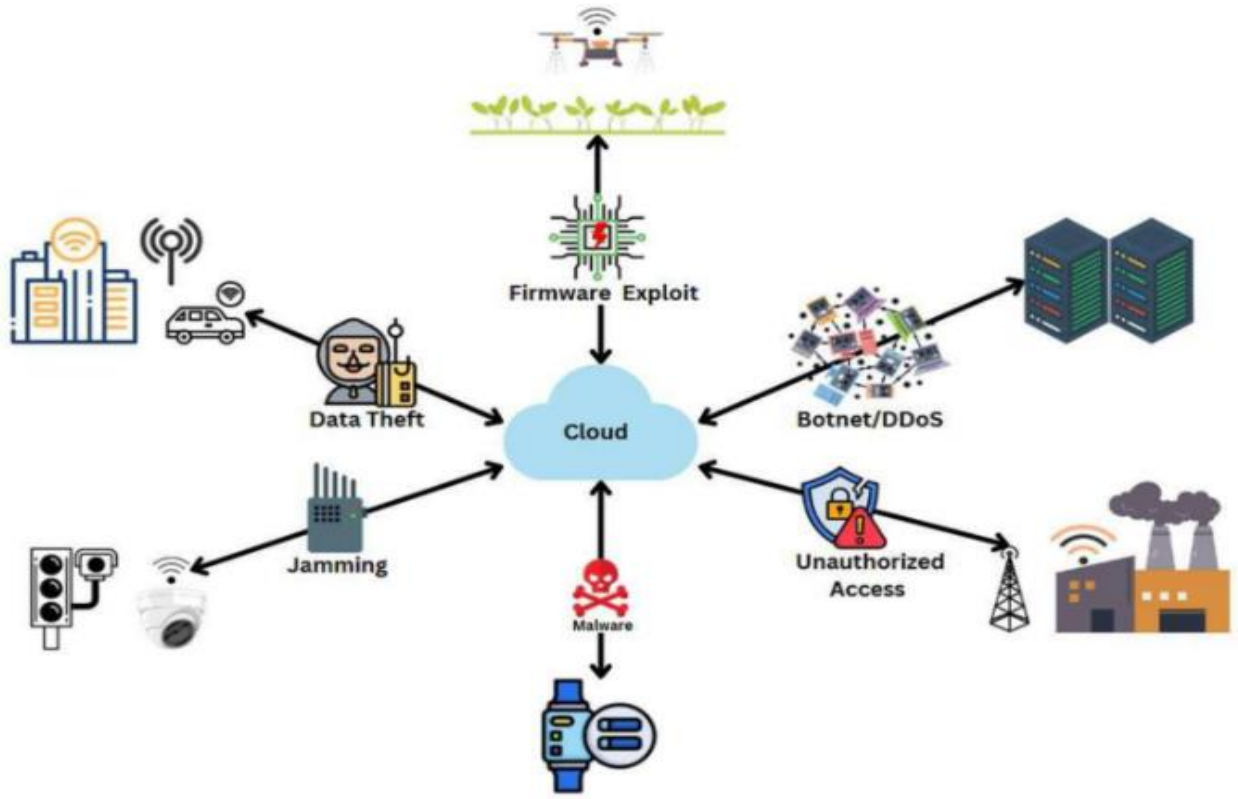

Fig 5: Security, Trust, and Safety of EdgeMind

5.1. Threat Model and Risk Mitigation

OS, user devices, and edge nodes represent cooperating digital representatives of human users, organizations, or autonomous agents acting in the real world. Users hand over part of their autonomy to these digital counterparts for configurable periods, allowing them to intelligently assist the user or execute predefined tasks in a flexible way, with the goal of allowing the user to control their environment more easily, efficiently, and securely. Such control can be exerted either directly or indirectly by

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receiving adapted information, notifications about the current state of the physical environment, or signals of noncompliance or critical danger.

The threat model operates under the presumption that none of the nodes can be fully trusted. Edge nodes constitute semi-honest trust domains with partial data-sharing requirements. Attackers can inject false or misleading data into the system, either by overpowering edge nodes or impersonating a user. Physical attacks on the sensor nodes are unlikely because they are small and spread over a large area. Denial-of-service attacks aim to slow down the network, cause unnecessary power drain, or make malfunctioning decisions. The goal must be to lower the number of possible exploits for the attackers and perform in-depth defense using a multilayer approach.

Equation 5: Trust score with provenance and experience

A linear trust fusion model is a natural formalization:

$$T_{ij} = \mu_1 A_j + \mu_2 R_j + \mu_3 M_{ij} + \mu_4 X_{ij} + \mu_5 P_{ij}$$

where:

- T_{ij}= trust of agent $i$in agent j
- A_j= authority
- R_j= reputation
- M_{ij}= messaging quality
- X_{ij}= direct transaction/service experience
- P_{ij}= provenance quality
- $\mu_r \geq 0$and $\sum_r \mu_r = 1$

Step-by-step derivation

From the text, trust is influenced by multiple measurable factors. So define each factor numerically.

If all factors are normalized into $[0, 1]$, then a weighted sum is suitable.

Weighted authority:

$$\mu_1 A_j$$

Weighted reputation:

$$\mu_2 R_j$$

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Weighted messaging quality:

$$\mu_3 M_{ij}$$

Weighted direct experience:

$$\mu_4 X_{ij}$$

Weighted provenance score:

$$\mu_5 P_{ij}$$

Add them:

$$T_{ij} = \mu_1 A_j + \mu_2 R_j + \mu_3 M_{ij} + \mu_4 X_{ij} + \mu_5 P_{ij}$$

If the weights sum to 1, then T_{ij} also stays interpretable on the same scale.

So the final trust equation is

$$\boxed{T_{ij} = \mu_1 A_j + \mu_2 R_j + \mu_3 M_{ij} + \mu_4 X_{ij} + \mu_5 P_{ij}}, \sum_{r=1}^{5} \mu_r = 1$$

5.2. Trust Frameworks and Provenance

Inter-agent trust is crucial for secure data sharing and collaborative decision-making. Several factors can shift the trust opinion of one agent towards another: the agent's own authority and reputation, information from other agents, quality of the agent's direct and indirect messaging, and transaction or service experiences. Direct service experiences can be modeled using standard trust metrics. In addition to the usual aggregation aspects, policies can specify how trust models evolve over time and how much historic data can be used in the future.

Provenance-based services can provide the necessary provenance information about the data, agents, and other entities associated with services. The trust model can be adapted to different attack models, for example, when the attacking agent has complete control over the system components handled directly by it and provides optimized updated parameters used for service learning. Provenance services can create and maintain verifiable logs to track the flow of data, control, and services through the system or record quantitative and qualitative data about the system and agents for future resource allocation. Such information can allow for the modeling of networks of trust (who to trust) and risk (who can corrupt the system).

5.3. Safety Guarantees and Fail-Safe Mechanisms

Safety contracts capture desirable safety properties expected from deployed intelligence. Requested and provided reliability metrics indicate the robustness of the model during testing and training. Upon detection of an intentional or unintentional attack on the service, the current state is rolled back to a state before the attack occurred.

In the event of a detected misuse, the service is isolated, and a fallback strategy is initiated. Dynamic approaches ensure appropriate rollbacks when memory resources gain quality decay. The proposed approaches help maintain model safety contracts throughout the service lifecycle. Safety criteria evolve as training data change over time and training with new data are required until the service is sufficiently tempered. These criteria are specified as safety contracts associated with the distributed intelligence component when deploying an application.

6. Evaluation and Validation Methodologies

Intelligence and adaptability are inherently difficult to evaluate and validate, especially in a distributed environment where components may evolve independently. The aim here is twofold: first, to provide a methodology for experimental research in distributed IoT environments; and second, to suggest metrics for assessing intelligence, adaptability, and efficiency. The resulting criteria apply to the EdgeMind framework, but they are also intended for more general use.

Dedicated distributed setups with resource-constrained edge devices (e.g., Raspberry Pis, Intel NUCs, NVIDIA Jetson Nano) are preferred. The proposed methodologies support a wide range of studies, including replication work (using the same setup and dataset as a prior study, but investigating different aspects), ablation experiments (decoupling agent learning or communication capabilities), and broader tests that control for EdgeMind's internal functioning without necessarily being considered replication studies.

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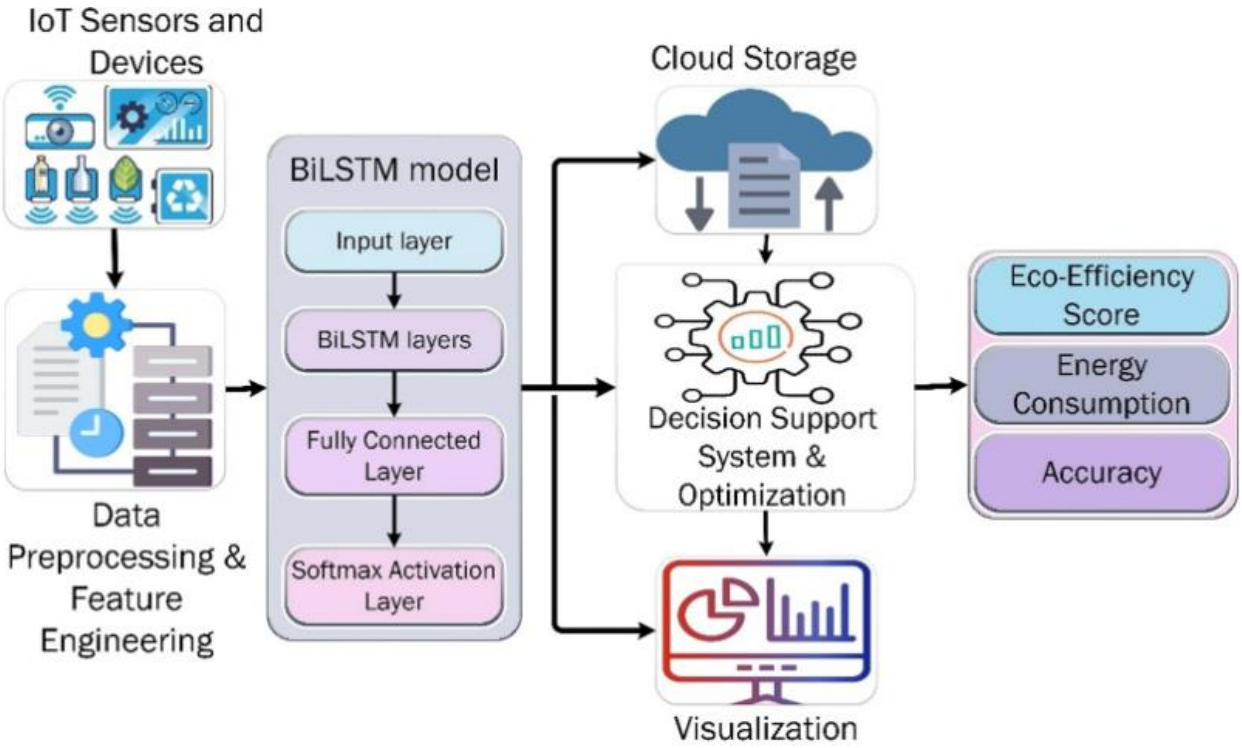

Fig 6: Evaluation and Validation Methodologies of EdgeMind

6.1. Experimental Design in Distributed IoT Environments

The EdgeMind Framework, with its data-sharing, resource-sharing, and governance interfaces, facilitates the design, deployment, and evaluation of distributed intelligence. Its case studies serve as a foundation for new applications. The scalability of a distributed intelligence ecosystem is being evaluated in a smart city pilot. A work-in-progress smart factory deployment focuses on the integration of existing edge resources with federated intelligence capabilities. Replication of the smart factory scenario on a different testbed (DULCE) assesses the portability of the EdgeMind approach, while an ablation study on distributed control investigates the impact of shared data.

Distributed intelligence is becoming critical as smart factories and smart cities evolve into large, heterogeneous ecosystems featuring information and communication technology and operational technology. Yet, the different nature of control and communication layers requires a fundamental shift in the design of machine intelligence toward a more distributed and data-centric paradigm. The EdgeMind Framework addresses these requirements by enabling self-evolving, distributed intelligence and, therefore, faster and risk-aware adaptation. These capabilities must be demonstrated and formally evaluated in large, heterogeneous environments that resemble EdgeMind deployments.

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6.2. Metrics for Intelligence, Adaptability, and Efficiency

Intelligence, effectiveness, and adaptability of EdgeMind-based solutions should be assessed via multiple measures, both qualitative and quantitative. A general testing framework designed for EdgeMind deployments can manage trade-offs across these metrics and identify best-suited solutions for specific application scenarios.

Primary applications fields include domains characterized by variability in both the involved resources (nodes) and the tasks handled. Consequently, EdgeMind-based intelligence should be considered as a system property emerging from cooperation. Intelligence, in this context, can be defined as the capability of a system — the result of many interconnected nodes working together — to perform tasks that, for single nodes, would require much longer times and possibly enormous quantities of resources. Therefore, while a specific particular node in the system may perform a task in a highly effective manner, the whole system may execute smart planning in the order of minutes and always with an acceptable level of quality. In other words, the whole system shows an intelligence that is higher than that of each single connected node, as no node can possibly be able to execute real-time planning. Consequently, smart planning in EdgeMind-based systems has to be quantitatively evaluated, and in particular in terms of task execution times and resources requested.

Feature	Federated Learning	Continual Learning	Meta-Learning
Data Sharing	Model updates only	Sequential tasks	Experience-based
Adaptation	Moderate	High	Very High
Privacy	Strong	Strong	Depends
Use Case	Distributed training	Dynamic environments	Fast adaptation

Table 3: Learning Paradigm Comparison

6.3. Case Studies and Benchmark Scenarios

Testing EdgeMind's mechanisms and behavior in distributed environments proving complex and risky remains crucial, especially in sensitive settings like healthcare. Several representative case studies support EdgeMind's deployment using practical experimentation. Their design considers system complexity, data-flow diversity, and operation modalities, covering the following focal areas: Smart Manufacturing, Smart Cities, and Healthcare.

Evaluation proceeds through application-relevant metrics—intelligence, adaptability, and efficiency. Validation examines EdgeMind's performance under user-specified conditions compared against alternative architectural approaches (e.g., Fully-Connected Topology, Cloud-Oriented Architecture) and non-collaboration strategies (e.g., Centralized Learning, Over-The-Air Learning).

Smart Manufacturing deployments address various need dimensions, align with specific KPIs, and integrate with existing facilities. Intelligence, Adaptability, and Efficiency encapsulate multiple aspects—collaboration, privacy, resource footprint; DRL-based decision making; resource constraints, continual learning—in a comprehensive 0–1 scale. Performance converging towards unity signals advancement and provision beyond Association Rule Learning-based (ARL) benchmarks.

Smart City supports a vast sensor ecosystem providing up-to-date information: weather, street conditions, traffic, public transport, crowd density, resource consumption, law enforcement. Distributed System Wrappers border EdgeMind-designed subnets, bundles of sensors, actuators, and Edge-Nodes executing throttle-accurate collective decisions. Evaluation scales across resource expensiveness and assesses user-centric outcome fulfilment.

In the Healthcare domain, EdgeMind can minimize Health Data exposure during distribution and improve monitoring and support quality for Seniors, minimizing supervision burdens.

7. Deployment Scenarios and Use Cases

Distributed intelligence is a promising implementation of AI technologies, with distinct features and advantages. Self-evolving, distributed agents are suitable for resource-constrained edge nodes, where learning data play a major role. The EdgeMind architecture adopts a layered structure to enable coordinated operation within larger-scale applications, such as Smart Manufacturing, Smart Cities, and Smart Healthcare. Sufficiently intelligent and adaptable agents reduce the requirement for centralized control, which, in specific scenarios, are more tailored to human needs, e.g., through participatory sensing or crowd-sourcing.

Reference deployments shed light on expected characteristics and desired key performance indicators (KPIs). For Smart Manufacturing, there is a focus on scalability and resilience within a distributed cybersecurity network, seamless addition of newly deployed sensors using conventional machine learning methods and intrusion-detection systems based on the federated-learning paradigm. In Smart Cities, the consideration is devoted to the implementation at the maturity level of a pilot laboratory, such as optimization of traffic-light management or pollution prediction. The architecture opens the door to a broad deployment roadmap in the domain of Healthcare Technologies and Services.

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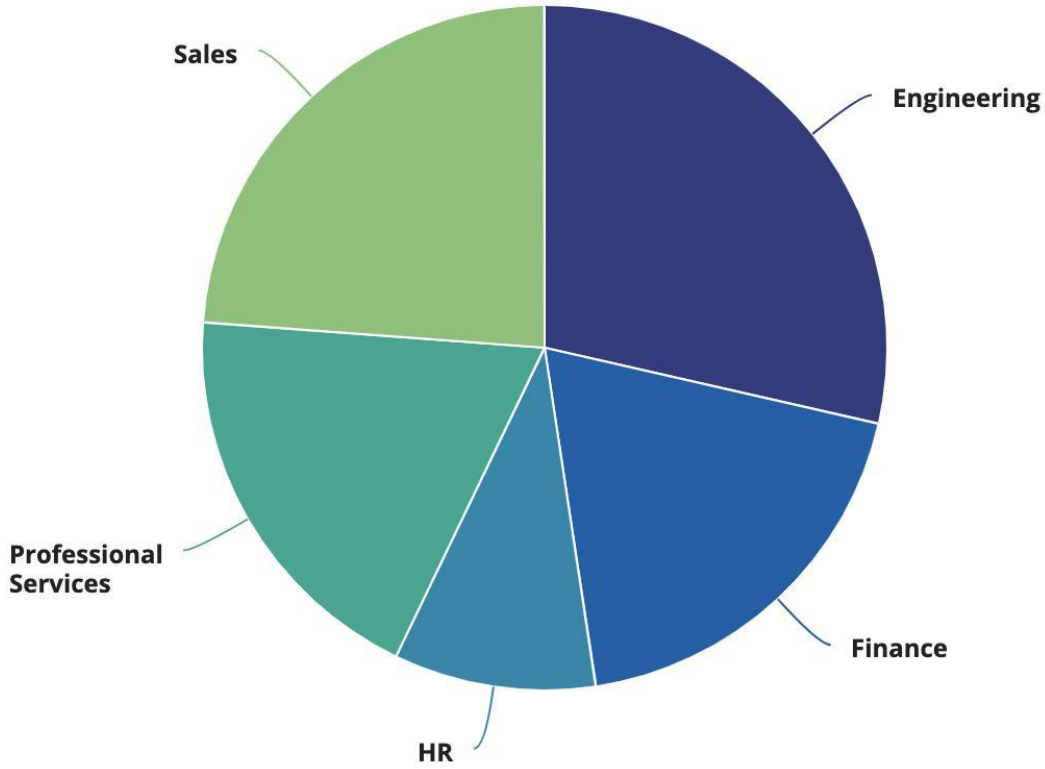

7.1. Smart Manufacturing and Industrial IoT

Manufacturing is an important domain for IoT adoption. Adopting smart solutions and increasing production efficiency is key to staying competitive. Rapid innovation requires costly R&D and the flexibility to quickly adapt production lines. Empirical research confirms that companies introducing smart solutions expect faster product development cycles, lower production costs, increased productivity, and higher quality. Nonetheless, Smart Manufacturing Systems are often confined to new facilities where all devices share the same technology, making it easier to build a security model.

The proposed deployment connects smart, sensitive devices to a graphic image for real-time monitoring, improving situational awareness. New smart solutions are paired with existing devices to enhance monitoring and decision-making. The AI player evaluates sensor data to improve process control, while alarms indicate the need for manual intervention. All devices remain separated and no additional resources are required. EdgeMind's high-speed processing and localized resource-intensive decision-making provide an advantage for the Smart Manufacturing System, allowing internal development and faster operation.

7.2. Smart Cities and Infrastructure

A deployment of EdgeMind in a major European urban area focuses on enhancing the resilience of critical infrastructure by employing IoT systems that can collectively detect failures and assist in recovery. The success metrics include the capacity to withstand an attack that disables some participants while still achieving consensus, alongside citizen trust in the underlying services. EdgeMind's distributed, decentralized architecture further minimizes a single point of failure in the event of a calamity.

EdgeMind's federated and continual learning mechanisms reduce communication overhead and provide implicit privacy guarantees for personal data, as information is shared in model weights rather than raw data samples. When proper conditions are met, self-optimization improves performance with minimal human intervention. Adaptation mechanisms that operate within local resource limits and support the cloud-edge continuum increase the system's operational efficiency. EdgeMind has also been deployed and benchmarked in other critical environments, with results that illustrate distributed intelligence advantages in IoT ecosystems. Such empirical validation remains limited so far, reinforcing the necessity of an extensive experimental agenda across diverse domains.

7.3. Healthcare and Assisted Living

For assisted living solutions, many privacy, safety, and regulatory variables should be considered to protect patients' sensitive and private information at the edge level. The presence of patients in training data (facial, behavioral, health related) must be taken with caution. The smart environment can also be used to train deep learning models for anonymity-preserving age and gender inference. Auxiliary information about individuals, such as the patient's area characteristics, can also be included in the modeling procedure in a privacypreserving manner. Human presence is used to decrease the cost associated with any model by embedding the decision-maker into the human loop, thus helping the system rapidly learn the desired decision based on few user queries. EdgeMind's ability to learn from others and from its own experiences and innovations opens the door to continuously learning new tasks with little or no need for retraining. It represents a smart lens to identify and mitigate potential obstacles when individuals are required to enter a protected zone.

In the case of a healthcare scenario, the proposed solution could make decisions on event passages, and provide feedback or warnings to the end user and/or the hospital. The data, especially video, noise levels, and event occurrence predictions, can also be considered for uploading when using cloud storage to update the model in a federated manner. The decision process of EdgeMind would focus on the areas where sensitive or private information would flow or pass to minimize privacy breaches. Furthermore, both the city and the hospital could assess the privacy of any newly generated model and the sensory device used for publishing data in the system. Recent studies have highlighted how future smart cities may become an influential partner for the previously introduced health smart regimes.

8. Conclusion

The emergence of new paradigms in artificial intelligence enables the transformation of communication networks into multi-agent systems programmed for learning and adaptation. Intelligence is distributed, and the dynamics are described in terms of learning loops rather than a single cognitive agent. The EdgeMind framework implements concepts of self-evolving intelligence and combines the benefits of federated and continual learning with elements of optimization and meta-learning. Two major principles define the EdgeMind architecture. First, the Flow-Resource Model encapsulates the tradeoffs between communication

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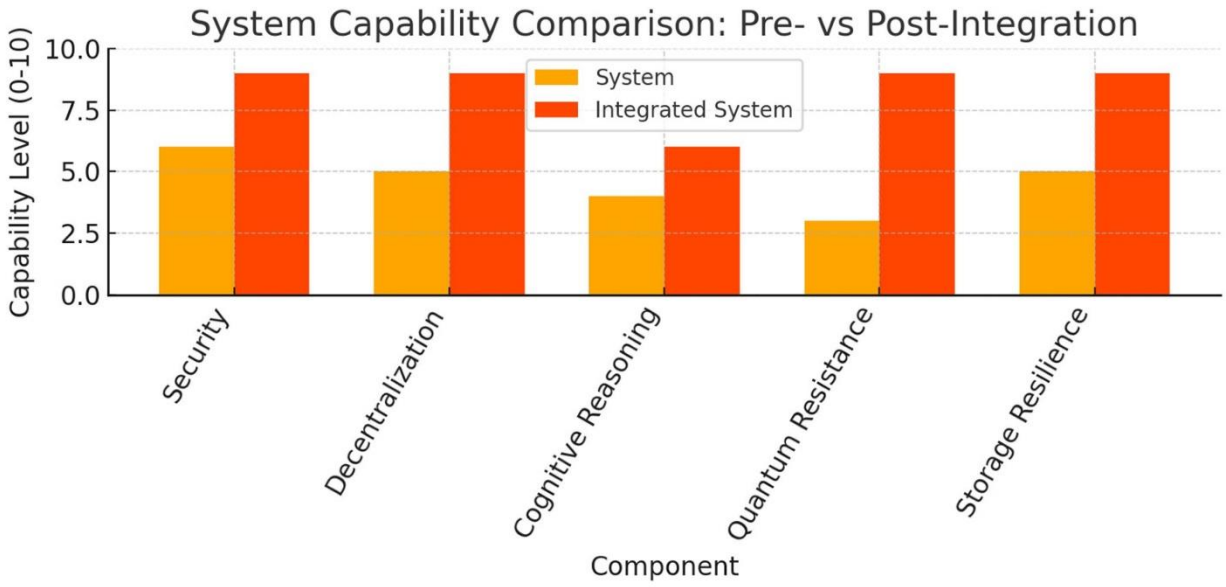
and computing efficiency and allows the system to self-optimize based on resource constraints of individual input-output agents. Second, the specialization of learning and adaptation processes coordinates agents' interactions according to their level of competence on a specific task.

Two vulnerabilities are paramount in emerging settings of distributed intelligence over the Internet of Things: risk exposure of at-risk devices and user distrust of data use. The study articulates elements of a trust framework built on trackable provenance and adds security perspectives to meta-learning by establishing a fail-safe mechanism. These ideas support a "safety by design" principle, extending the concept of privacy by design to artificial intelligence. A three-step experimental paradigm—with dedicated testbeds for deployment in real-world environments—provides methodologies for answering EdgeMind-related research challenges. The first step investigates intelligence and adaptability, and the second analyzes efficiency. Distributed deployment in smart manufacturing and industrial Internet of Things environments represents a primary application, while additional scenarios include smart cities and infrastructures, healthcare, and assisted living.



8.1. Emerging Trends

A modular, self-evolving, distributed-intelligence framework for IoT ecosystems was described, along with a preliminary approach for evaluation and validation. Representative deployments in smart manufacturing, smart cities, and healthcare were outlined. EdgeMind systems are intended to automate intelligence at the edge across an edge-cloud continuum, with minimal human intervention. Research questions thus addressed were: to what extent can the EdgeMind design be used for self-governing, self-evolving, multi-IoT systems that harness distributed intelligence, adapt continuously, and operate with minimal human supervision in IoT ecosystems? When integrating EdgeMind with existing facilities, capabilities must adapt intelligently to the scene while optimizing resource utilization.

Trends indicate that proprietary and centralized systems are giving way to open-source paradigms based on standards. Reinforcement-learning methods for teaching new skills are experiencing rapid advances. Enabling technologies for the EdgeMind concept, including edge/cloud collaboration, federated and continual learning, trust and safety technologies, and private-by-design systems, are rapidly maturing. Internet censorship and monitoring are pushing research and applications toward privacy-preserving mechanisms. IoT infrastructure investment is expected to exceed augmented reality/virtual reality, robotics, and blockchain combined. However, even within an industry-favored sector, product-focused, islanded deployments of IoT solutions are failing to deliver expected returns. Such systems lack interoperability and leaf-side intelligence, foreclosing low-power and low-latency solutions. Emerging decentralized data-storage techniques may reduce dependence on centralized storage for database-driven applications.

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