UNIVERSITÀ DELLA CALABRIA
DIPARTIMENTO DI INGEGNERIA INFORMATICA, MODELLISTICA, ELETTRONICA E SISTEMISTICA
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From Digital Twins to Generative Digital Twins: Towards a Novel Approach in the IoT Edge-Cloud Continuum

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UNIBO – Comp. Science and Engineering Dept. – Bologna - Feb 3, 2025

The SPEME laboratory

https://speme.dimes.unical.it/

- The **SPEME (Smart, PErvasive and Mobile systems Engineering)** Lab has a global “mission”: the development of innovative methods and systems for engineering trustworthy, distributed, intelligent, pervasive, mobile, multimedia and multi-sensorial systems.
- The **current research lines** are both methodological and experimental and include the following themes: Internet of Things, Wearable computing, Agent-based computing, Signal processing of physiological signals, Internet of Vehicles, Radiomics, Blockchains, Cyber/IoT Security.
- **Group members** (40+): 1 Full prof.; 3 Associate prof.; 1 Tenured Assistant prof.; 2 Adjunct prof.; 3 Assistant prof; 11 Postdocs/RA; 18 Phd students; 1 laboratory research assistant.
- **Members’ Nationalities**: Italy, India, Colombia, Pakistan, China, Bangladesh, Romania
- **Projects**: 2 Horizon Europe; 4 PRIN (Minister of University and Research); 1 POS (Minister of Health); 5 PNRR (National Resilience & Recovery Plan); 10+ Industry projects = 10+ Meuros
- **International collaborations**: USA (6), Canada (1), South America (2), UK (5), EU (10+), China (7), Australia (3), Saudi Arabia (3), Morocco (3), etc.

The SPEME laboratory

Outline

1. Towards Edge Intelligence (EI)[a] for IoT Systems of Systems[b]
2. Integrating ML and Multi-Agent Systems [e]: the EU MLSysOps Project
3. From Digital Twins to Opportunistic Digital Twins[c]
4. Towards Generative Digital Twins[d]
5. Concluding Remarks

[a] V. Barbuto, C. Savaglio, M. Chen, G. Fortino: Disclosing Edge Intelligence: A Systematic Meta-Survey. Big Data Cogn. Comput. 7(1): 44 (2023)

[b] G. Fortino, C. Savaglio, G. Spezzano, M. Zhou: Internet of Things as System of Systems: A Review of Methodologies, Frameworks, Platforms, and Tools. IEEE Trans. Syst. Man Cybern. Syst. 51(1): 223-236 (2021)

[c] C. Savaglio, V. Barbuto, F. M. Awan, R. Minerva, N. Crespi, and Giancarlo Fortino. 2023. Opportunistic Digital Twin: an Edge Intelligence enabler for Smart City. ACM Trans. Sen. Netw. Just Accepted (August 2023). https://doi.org/10.1145/3616014.

[d] C. Savaglio, V. Barbuto, F. Mangione and G. Fortino, "Generative Digital Twins: A Novel Approach in the IoT Edge-Cloud Continuum," in IEEE Internet of Things Magazine, vol. 8, no. 1, pp. 42-48, January 2025, doi: 10.1109/IOTM.001.2400035.

[e] G. Fortino, W. Russo, C. Savaglio, W. Shen, M. Zhou: Agent-Oriented Cooperative Smart Objects: From IoT System Design to Implementation. IEEE Trans. Syst. Man Cybern. Syst. 48(11): 1939-1956 (2018)

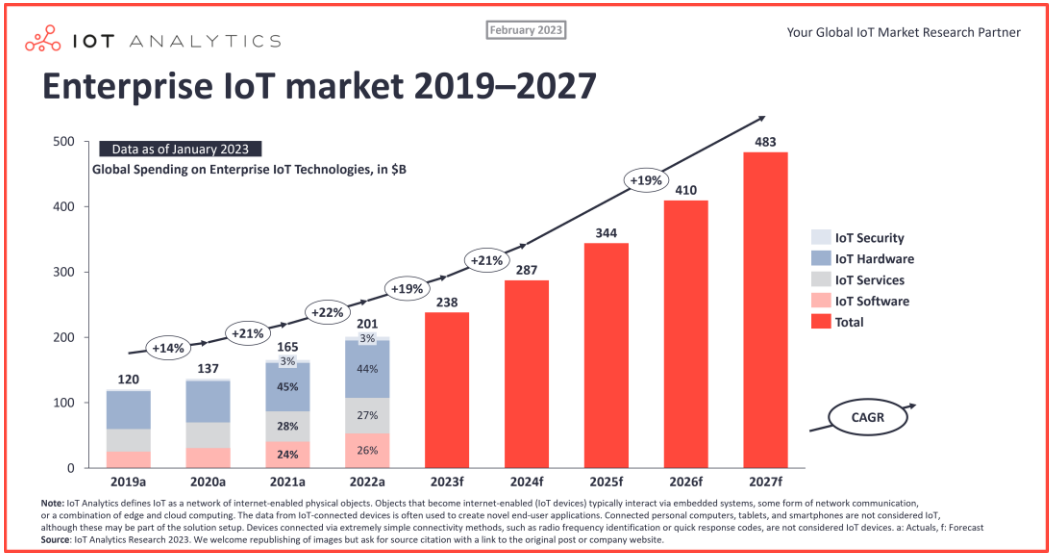
Internet of Things: Definition and Characteristics

*“The **Internet of Things (IoT)** is a novel paradigm that involves the pervasive presence of a variety of objects or things, sensors, actuators, and mobile phones, which can interact and cooperate with each other to achieve common goals.” (Atzori et al., 2010)*

***My definition**: “A loosely coupled, decentralized system of cooperating smart objects (SOs). Cooperating SOs are autonomous, physical digital objects augmented with sensing/actuating, processing, storing, and networking capabilities able to sense/actuate, store, and interpret information created within themselves and around the neighboring external world where they are situated, act on their own, cooperate with each other, and exchange information with other kinds of electronic devices and human users.”*

- Since the 2000s, tech advancements have driven IoT's growth:
  - **1st IoT Gen**: Miniaturized, cost-effective components like wireless sensors, RFiD systems, micro-controllers, and processors integrated into consumer electronics.
  - **2nd and 3rd IoT Gen**: Integration into broader systems (ERP[1], supply chain) powered by synergy AI, signal processing, distributed computing, and big data analytics.
  - **Next Gen:** AI and EdgeAI-driven IoT

Internet of Things: Definition and Characteristics



Global IoT market size to grow 19% in 2023—IoT shows resilience despite economic downturn. Source: IoT Analytics

- **IoT Numbers** (Mordor Intelligence, 2021)
  - Billions of deployed devices (smart homes, cars, factories).
  - A trillion-dollar market, resilient to crises (e.g., COVID-19).
  - Substantial investments in enabling tech (5G, Wi-Fi 6, AR, etc.).
- **IoT Research Perspectives** (Atzori et al., 2010)
  - Thing-Oriented: Object visibility and traceability.
  - Internet-Oriented: Ubiquitous networking.
  - Semantic-Oriented: Data representation and processing.

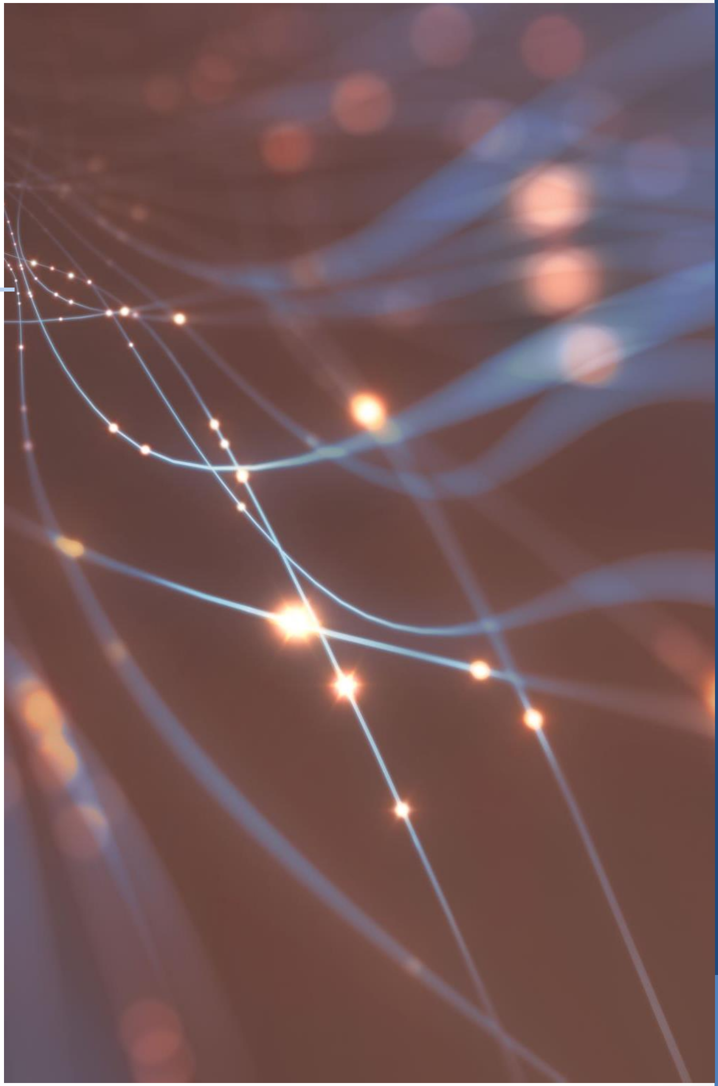
Final Goal

Fueling an IoT ecosystem where humans and machines – equipped with autonomic and cognitive skills – seamlessly connect within an endless stream of information.

Ubiquitous Data/Information Generation

- **Problem**
  - Over **150 billion** connected devices generate more than **90 Zettabytes** of data at the network Edge[1].
  - Data are moving to a **network of ubiquitous device**
  - Need to **rethink analysis** and **processing methods** to keep up with the **increasing amount and speed of data**

- **Solution**
  - Move **computation rather the data**, i.e., bring **intelligence as close as possible to data sources**.

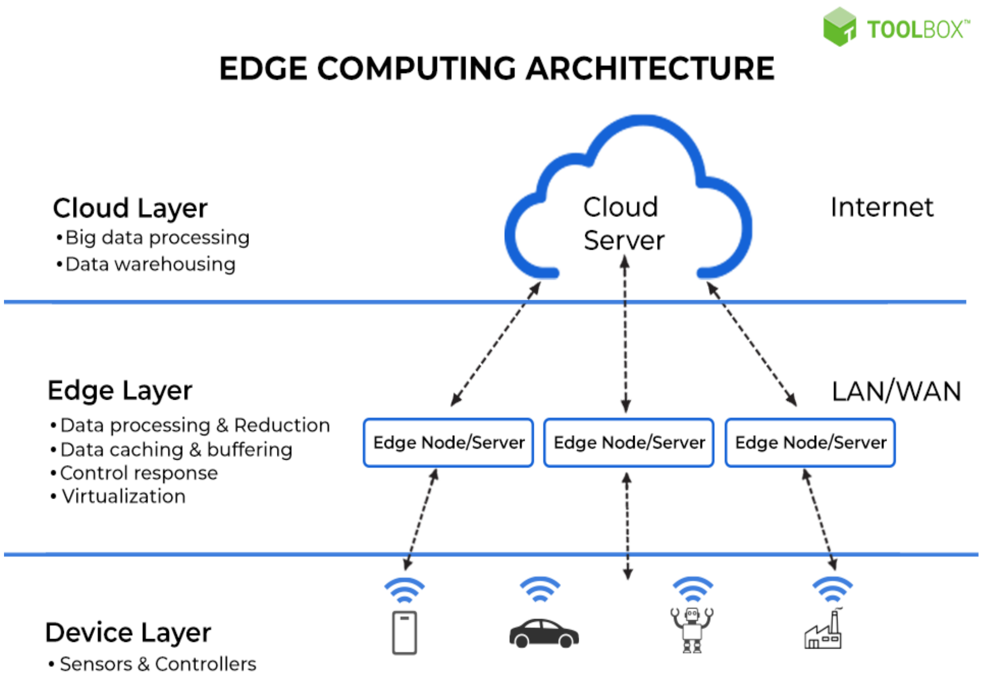


1. The Digitization of the World from Edge to Core

EDGE COMPUTING

"A distributed computing paradigm that ***brings computation*** *and data storage* ***at the edge of the network****, improving speed, efficiency, and cost savings".*

- It offers **several benefits over traditional cloud computing**, including:
  - **faster response times**;
  - improved **reliability**;
  - and enhanced **data security**.
- It presents **some challenges**, such as:
  - managing **many distributed devices**;
  - and **ensuring data consistency** across the network.



Source: [What is Edge Computing?]

INTELLIGENCE AND AI

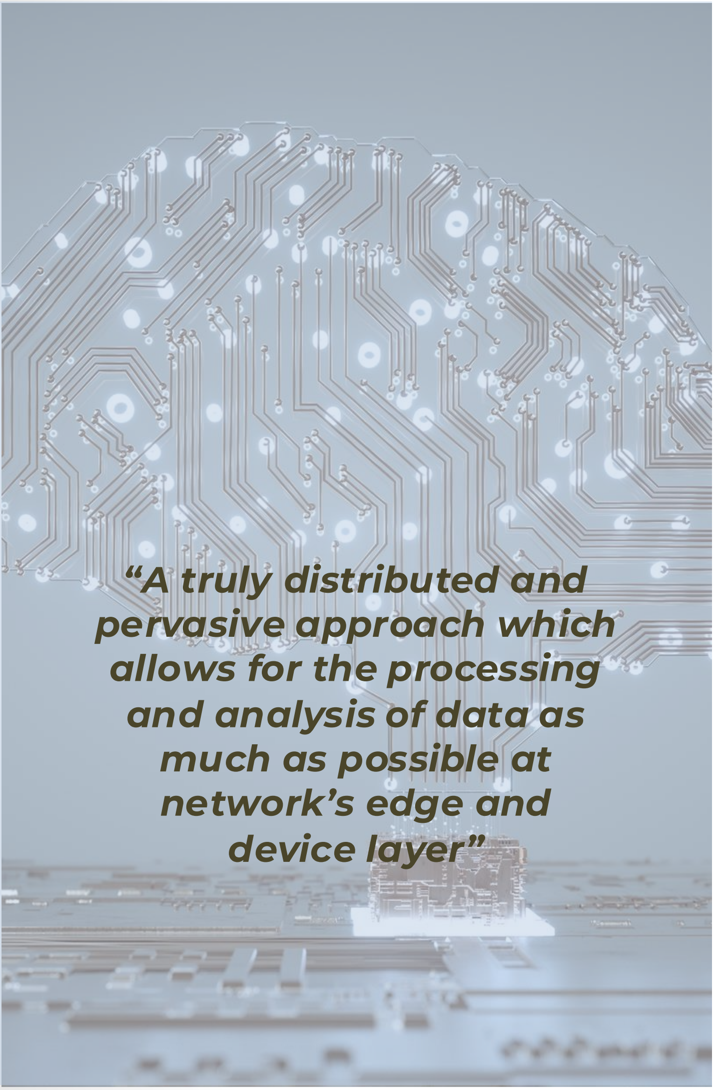
- **Intelligence**[1]
  - it belongs to a subject and **measures the subject's ability to interact with its environment;**
  - it **measures the capability to set and reach objectives;**
  - it **characterizes** the ability to **adapt behavior in response to the environment**;

Artificial Intelligence (AI) typically simulates human intelligence by demonstrating some of the following behaviors[2]:

1. **Planning**
2. **Learning** (through Training)
3. **Reasoning**

1. Zhi Zhou, Xu Chen et. al. "Edge intelligence: Paving the last mile of artificial intelligence with edge computing."
2. Ella Peltonen, Ijaz Ahmad et. al. "The Many Faces of Edge Intelligence"

EDGE INTELLIGENCE - EI



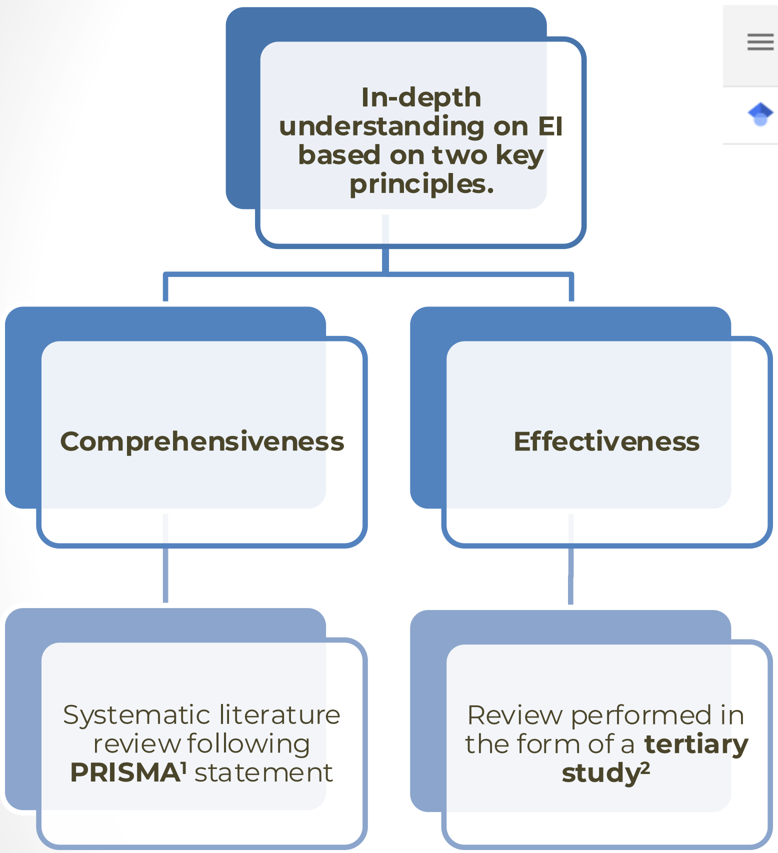
Main features

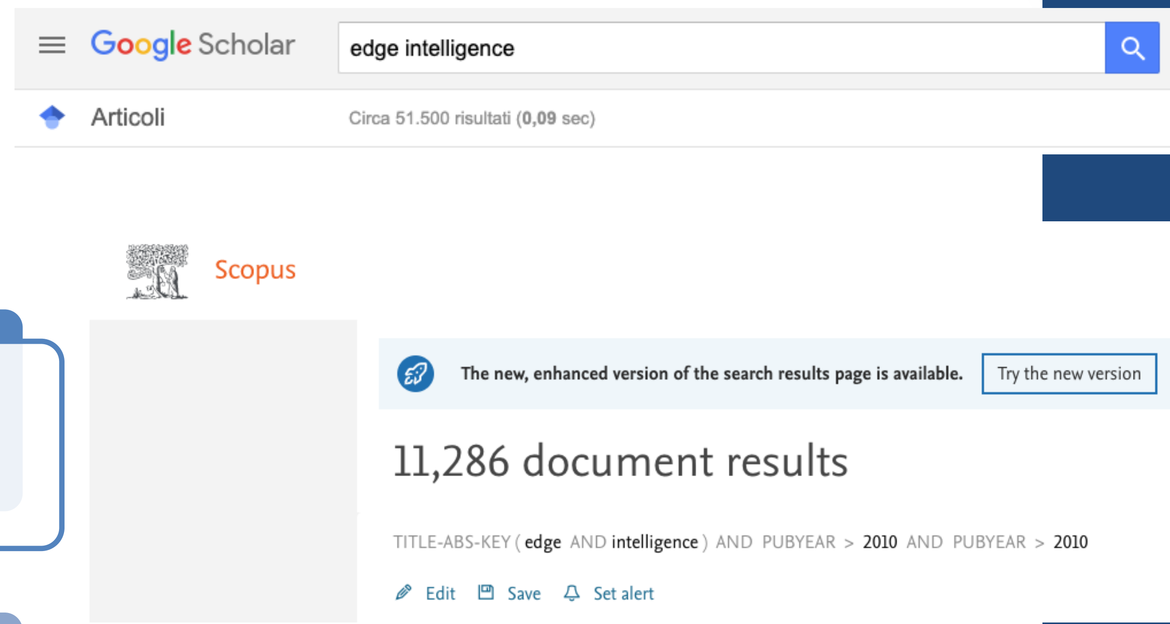
- **Real-time** data **processing** and **analysis**
- **Low latency** and **high throughput**
- **Edge-to-cloud** integration
- **Flexible deployment** options
- Advanced **security** and **privacy features**.

Benefits

- Improved **data insights** and **decision-making**
- Increased **operational efficiency**
- Reduced **costs**, **latency** and **data traffic**
- Enhanced **privacy** as well as **scalability** and **reliability**

Systematic meta-survey on EI*

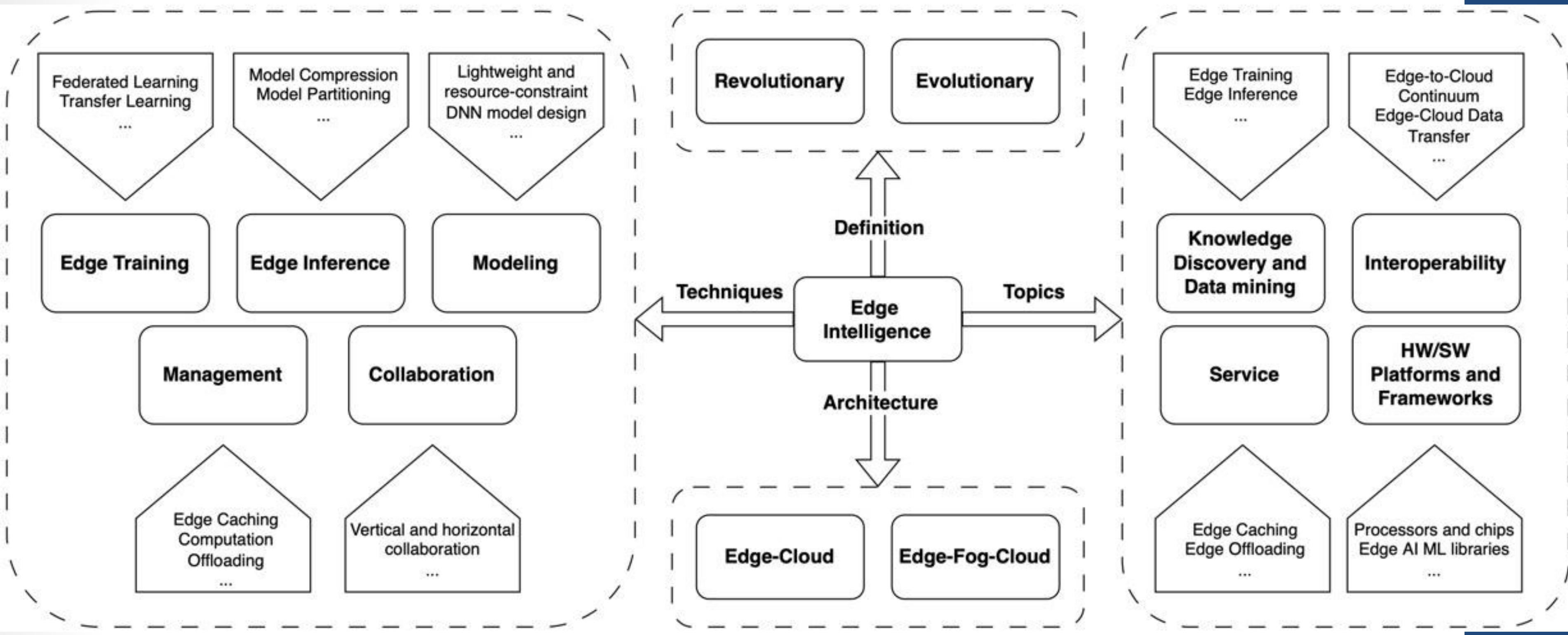




1. A guideline for conducting and reporting systematic reviews and meta-analyses
2. aggregates and generalizing the main results from large collections of thematically related secondary studies

*V. Barbuto, C. Savaglio, M. Chen, G. Fortino: Disclosing Edge Intelligence: A Systematic Meta-Survey. Big Data Cogn. Comput. 7(1): 44 (2023)

RQs OVERVIEW



FRAMEWORK (1/2)

Reference	Year	# Citations	Systematic Literature Review	EI Definition	Reference Architecture	Topics Addressed	Key Techniques	Hardware Tools	Software Tools	Use cases
Edge Intelligence: Paving the Last Mile of Artificial Intelligence With Edge Computing	2019	703	No	**Revolution:** "The marriage of edge computing and artificial intelligence"	Yes: Two-layer architecture	• KDD • Platforms/ Frameworks	• Edge Training • Edge Inference	• Edge devices	• Systems and Frameworks on EI Model Training • Systems and Frameworks on EI Model Inference	• Smart factory • Smart city • Smart home • Entertainment
OpenEI: An open framework for edge intelligence	2019	47	No	**Evolution:** "The capability to enable edges to execute AI algorithms"	No	• Interoperability • Platforms/ Frameworks	• Edge Training • Edge Inference • Modeling	• Hardware modules	• Running environments • Edge-based deep learning packages	• Automotive • Smart home • Healthcare • Public Safety
Edge Intelligence: The Convergence of Humans, Things, and AI	2019	25	No	**Revolution:** "A new paradigm in which intelligence is gradually be pushed from the cloud closer to the edge"	No	• Outlook • Platforms/ Frameworks	N.A	• Edge AI chips and modules	• Tools for Managing the AI Lifecycle • Edge Computing platforms	• Smart City • Automotive • Healthcare • Corporate
Edge Intelligence	2019	0	No	**Revolution:** "Edge computing with machine learning and advanced networking capabilities"	Yes: Two-layer architecture	• Standardization	N.A	• Edge devices	N.A	• Smart factory • Smart city • Public Safety
Convergence of Edge Computing and Deep Learning: A Comprehensive Survey	2020	486	No	**Revolution:** "The combination of edge computing and artificial intelligence"	Yes: Two-layer architecture	• KDD • Platforms/ Frameworks • Service • Outlook	• Edge Training • Edge Inference • Management • Collaboration	• AI Hardware for Edge Computing	• Edge frameworks for DL	• Smart city • Automotive • Smart home • Smart factory
Edge Intelligence: The Confluence of Edge Computing and Artificial Intelligence	2020	239	No	**Revolution:** "The integration between edge computing and artificial intelligence"	No	• KDD • Service	• Edge Inference • Management	N.A	N.A	• Automotive • Smart home • Smart city
Edge Intelligence: Challenges and Opportunities	2020	1	No	**Evolution:** "The next stage of edge computing, which allows to run AI applications at the edge of the network"	Yes: Three-layer architecture	• KDD • Platforms/ Frameworks • Service	• Edge Training • Edge Inference • Modeling	• Edge AI chips • Edge Computing Platforms	• Edge AI Programming libraries	• Automotive • Smart factory • Smart city • Healthcare

FRAMEWORK (2/2)

Reference	Year	# Citations	Systematic Literature Review	EI Definition	Reference Architecture	Topics Addressed	Key Techniques	Hardware Tools	Software Tools	Use cases
Edge Intelligence: A Robust Reinforcement of Edge Computing and Artificial Intelligence	2021	0	No	**Revolution:** "A new outlook risen by the combination of edge computing and artificial intelligence"	No	• KDD • Service	N.A	N.A	N.A	• Automotive • Military
Edge Intelligence: Empowering Intelligence to the Edge of Network	2021	19	No	**Revolution:** "Refers to a set of connected systems and devices for data collection, caching, processing, and analysis proximity to where data are captured based on artificial intelligence."	Yes: Two-layer architecture	• KDD • Service	• Edge Training • Edge Inference • Modeling • Management	N.A	N.A	• Smart factory • Smart city • Healthcare
The Many Faces of Edge Intelligence	2022	0	No	**Evolution:** "An emerging computing paradigm that enables AI functionalities at the network edge"	Yes: Three-layer architecture	• Outlook	N.A	N.A	N.A	• Smart city • Automotive
Artificial Intelligence in the IoT Era: A Review of Edge AI Hardware and Software	2022	2	No	**Evolution:** "The modern trend of moving artificial intelligence computation near to the origin of data sources"	No	• Platforms/ Frameworks • Outlook	• Edge Inference	• Hardware devices • NVIDIA Jetson devices	• ML Frameworks • Mobile SDK • Software for MCU • Model conversion libraries for MCU	N.A
Roadmap for edge AI: A Dagstuhl Perspective	2022	8	No	**Revolution:** "A fast evolving domain that merges edge computing and artificial intelligence (or machine learning)"	No	• Outlook	N.A	N.A	N.A	• Automotive • Entertainment • Smart Factory • Healthcare
Distributed intelligence on the Edge-to-Cloud Continuum: A systematic literature review	2022	8	Si	N.A	No	• KDD • Interoperability • Platforms/ Frameworks	• Edge Training • Edge Inference • Modeling • Collaboration (All are indirect contributions)	• Edge devices • Processors	• Software for Machine Learning on the Edge-to-Cloud Continuum • Frameworks/ Libraries for Data Analytics on the Edge-to-Cloud Continuum • Simulation and Emulation systems	• Healthcare • Smart factory • Smart agriculture • Smart cities • Automotive
Edge Intelligence: Concepts, Architectures, Applications, and Future Directions	2022	4	No	**Revolution:** "the confluence of edge computing with machine learning, or artificial intelligence (AI) in the broad sense"	Yes: Two-layer architecture	• KDD • Platforms/ Frameworks • Outlook	• Edge Training	• Edge devices	• Edge Intelligence Frameworks	• Automotive • Entertainment • Smart home • Smart city • Smart factory

*V. Barbuto, C. Savaglio, M. Chen, G. Fortino: Disclosing Edge Intelligence: A Systematic Meta-Survey. Big Data Cogn. Comput. 7(1): 44 (2023)

Lessons learnt

- **IoT systems** and related services **require effective intelligence** to **unleash** their potential.
- **Edge Intelligence** emerges as a **new, highly promising field** with broad **appeal** and **usefulness**.
- This survey analyzed the **last decade's literature on EI** using both **quantitative** and **qualitative** methods based on **PRISMA** guidelines.
- Although **ETSI MEC** provides a **solid base for EI**, it **lacks built-in intelligence** for edge system.

*V. Barbuto, C. Savaglio, M. Chen, G. Fortino: Disclosing Edge Intelligence: A Systematic Meta-Survey. Big Data Cogn. Comput. 7(1): 44 (2023)

Lessons learnt

- Further specifications are needed for **standardized APIs**, **software constructs**, and **supporting infrastructures**.

- The latest concept of the ***edge-cloud continuum*** may **lead to** isomorphic **EI architectures**, dissolving the boundaries between the cloud and edge.

The research leading to this work was carried out under the Italian MIUR, PRIN 2017 Project "Fluidware" (CUP H24I17000070001), and under the "MLSysOps Project" (Grant Agreement 101092912) funded by the European Community's Horizon Europe Programme.

*V. Barbuto, C. Savaglio, M. Chen, G. Fortino: Disclosing Edge Intelligence: A Systematic Meta-Survey. Big Data Cogn. Comput. 7(1): 44 (2023)

The Device-Edge-Cloud continuum

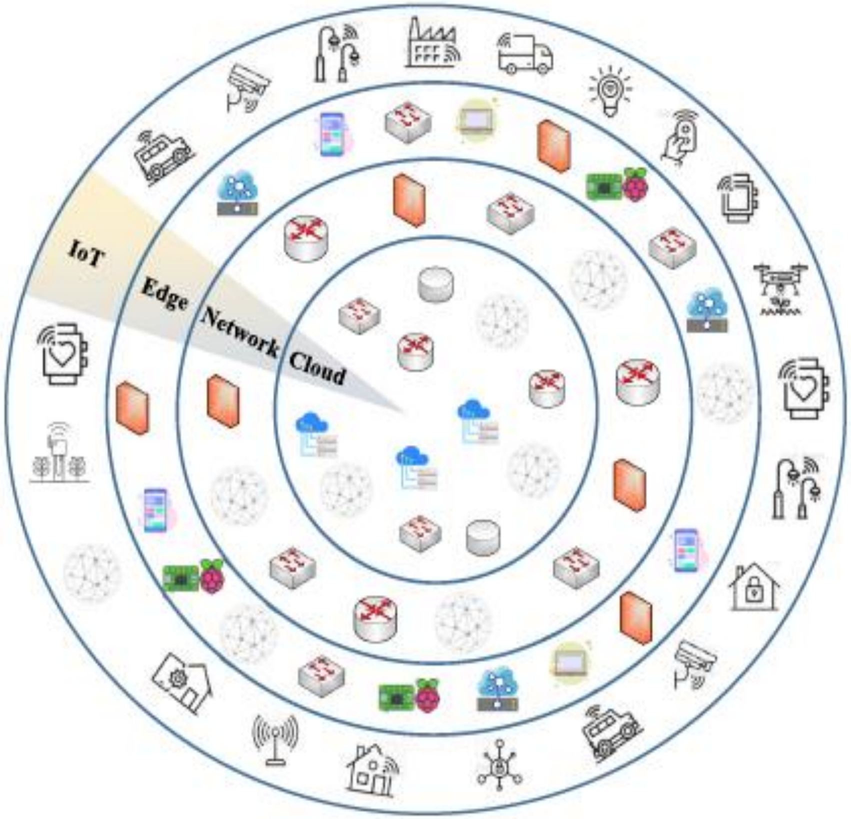


Fig. 1. 4-tier architecture — the outer layer is composed of IoT devices generating data and transmitting these to Edge devices (second layer). The Innermost layer is comprised of a Cloud datacenter, with a data network connecting these layers.

Khaled Alwasel, Devki Nandan Jha, Fawzy Habeeb, Umit Demirbaga, Omer Rana, Thar Baker, Scharam Dustdar, Massimo Villari, Philip James, Ellis Solaiman, Rajiv Ranjan, IoTSim-Osmosis: A framework for modeling and simulating IoT applications over an edge-cloud continuum, Journal of Systems Architecture, Volume 116, 2021, https://doi.org/10.1016/j.sysarc.2020.101956.

The Device-Edge-Cloud continuum

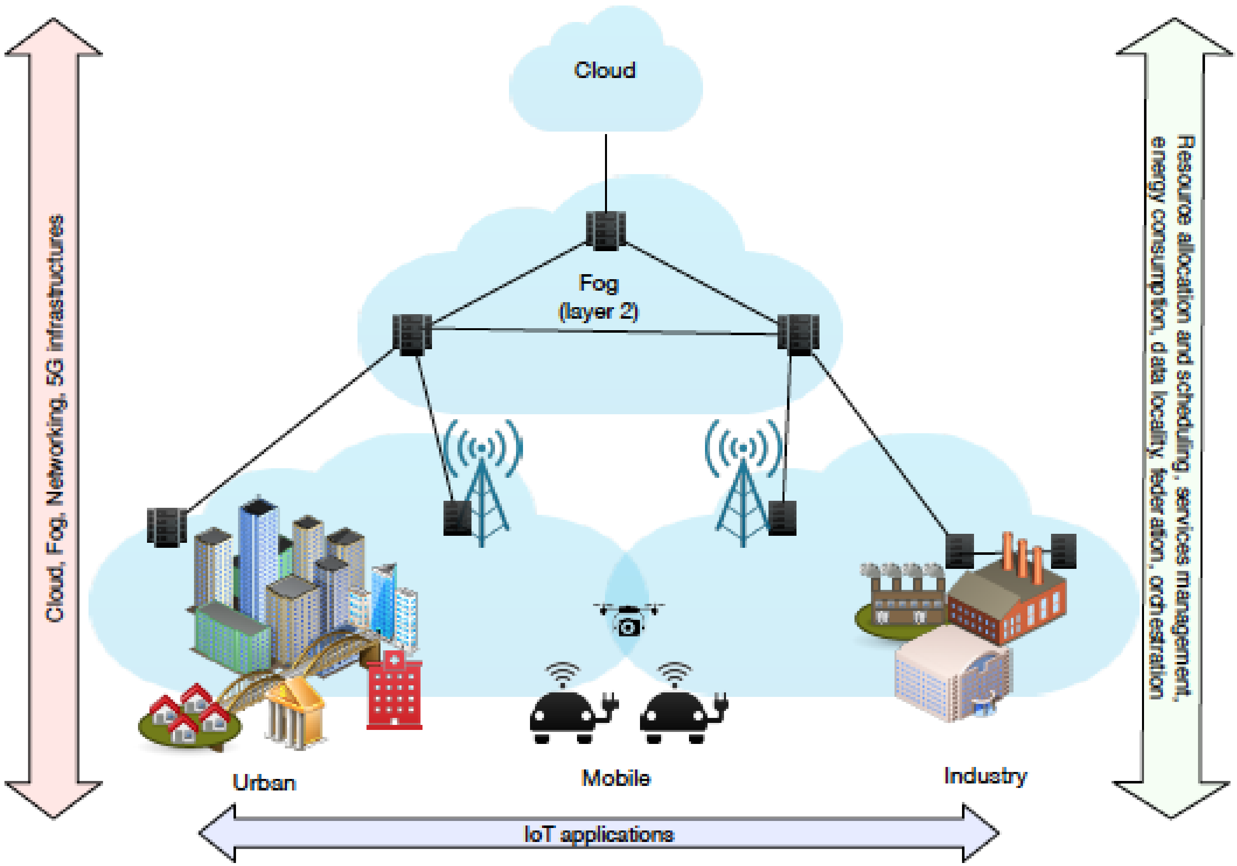


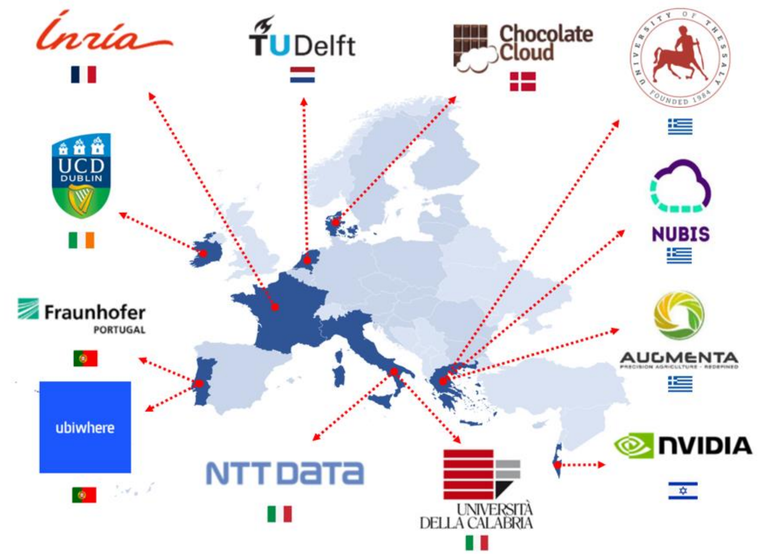
Figure 1: Illustrative overview, within the IoT-Fog-Cloud infrastructure, of topics covered in this paper.

Luiz Bittencourt, Roger Immich, Rizos Sakellariou, Nelson Fonseca, Edmundo Madeira, Marilia Curado, Leandro Villas, Luiz DaSilva, Craig Lee, Omer Rana, The Internet of Things, Fog and Cloud continuum: Integration and challenges, Internet of Things, Volumes 3–4, 2018, Pages 134-155, https://doi.org/10.1016/j.iot.2018.09.005.

Machine Learning for Autonomic System Operation in the Heterogeneous Edge-Cloud Continuum (MLSysOps)

Giancarlo Fortino
Deputy Coordinator of the Project
University of Calabria

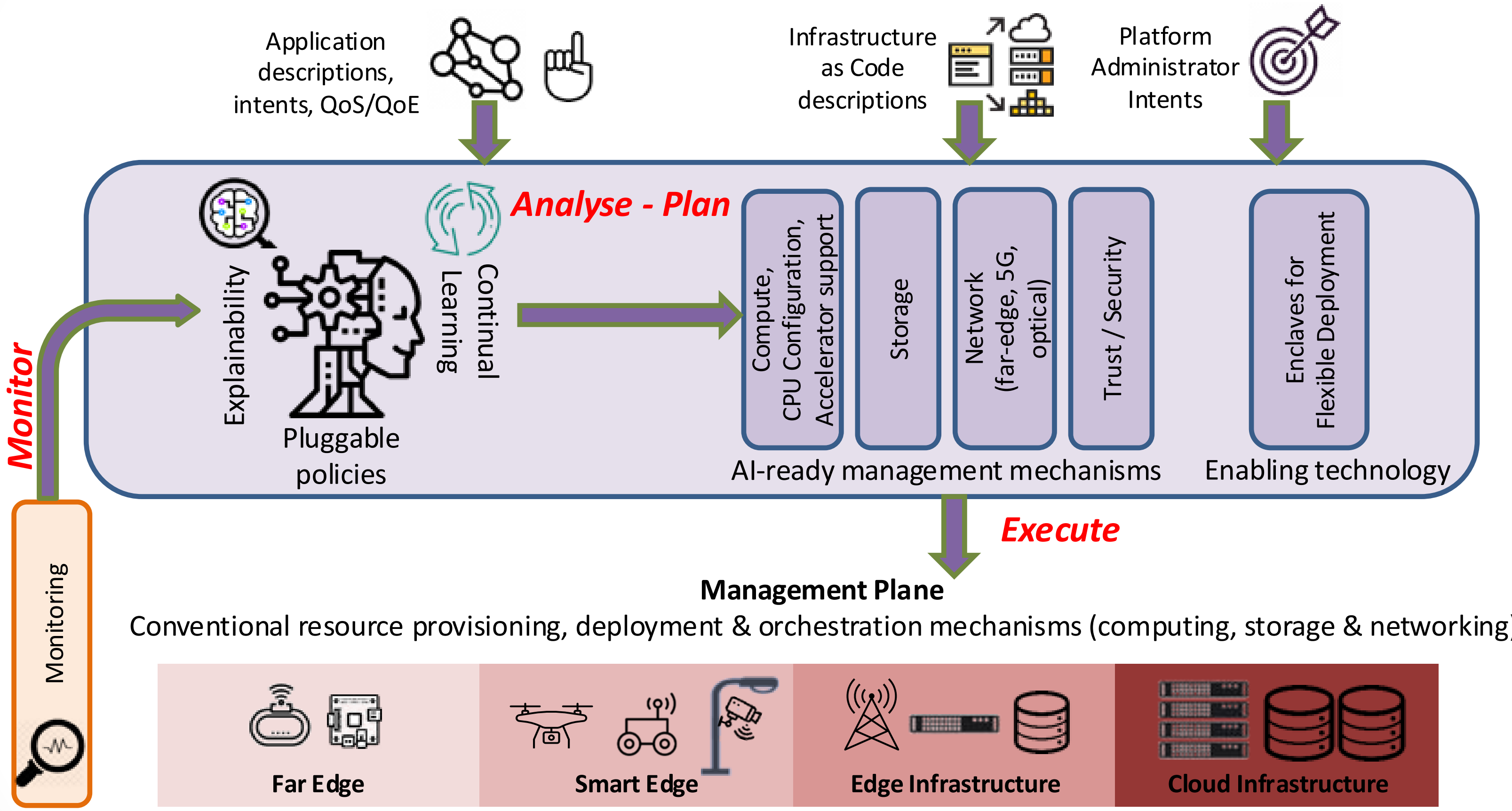
Consortium



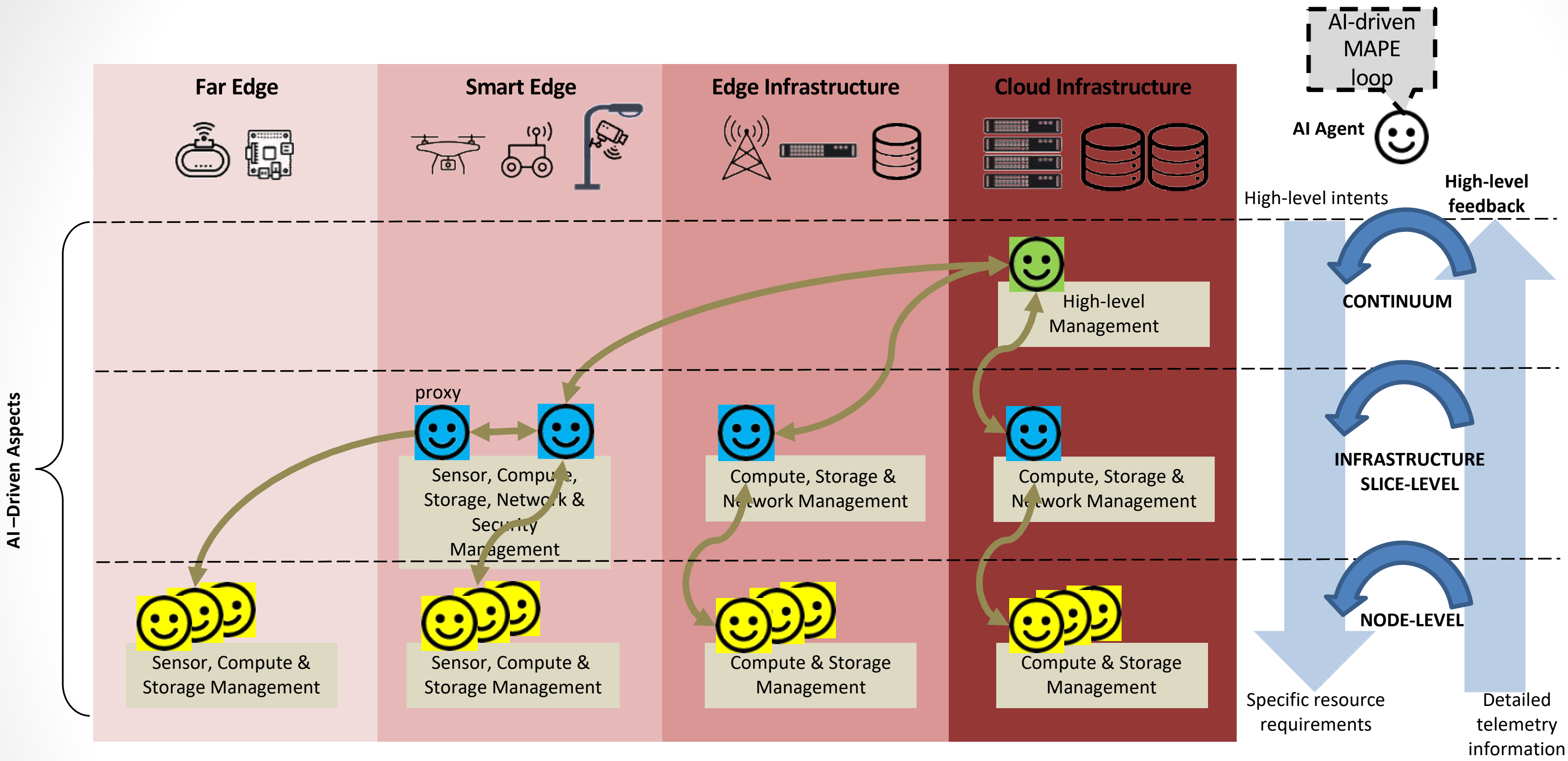
Channels

https://mlsysops.eu/
https://www.linkedin.com/company/mlsysops/
https://twitter.com/mlsysops

MLSysOps High-level Architecture

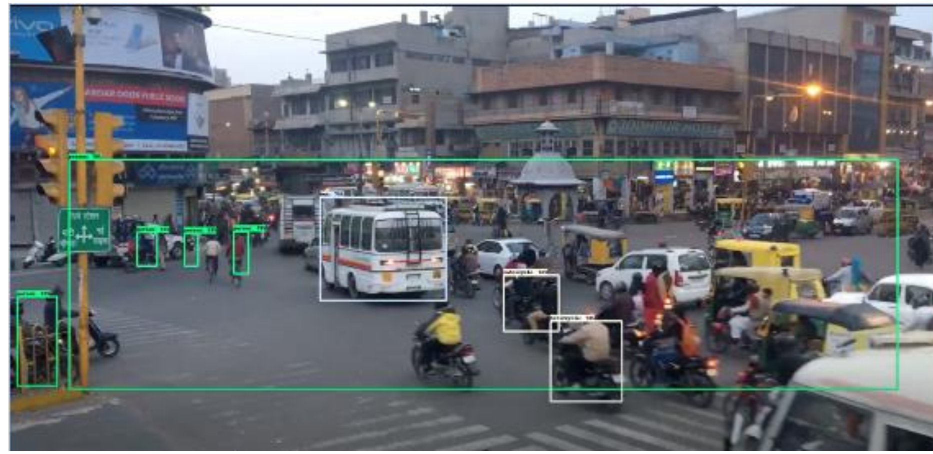


Agent-based Architecture



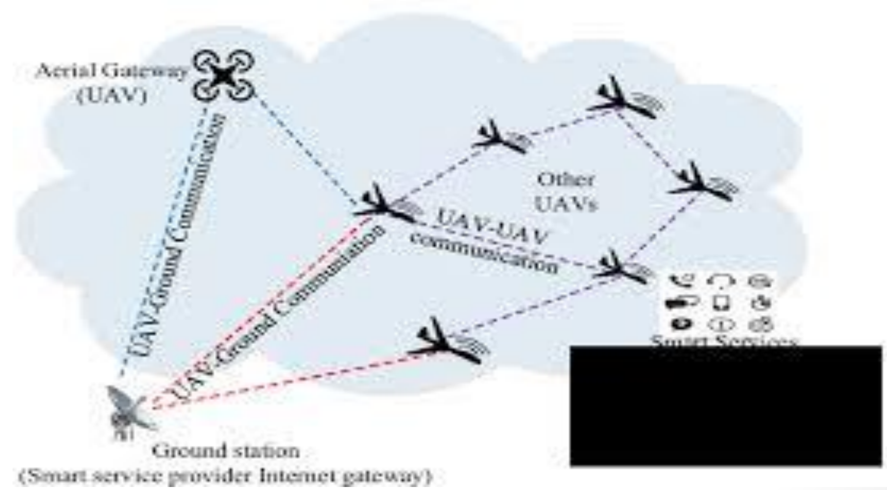
Use Cases

Smart Agriculture



Smart City

Smart Wearable Systems



Smart Drone Systems

From Digital Twins to Opportunistic DTs

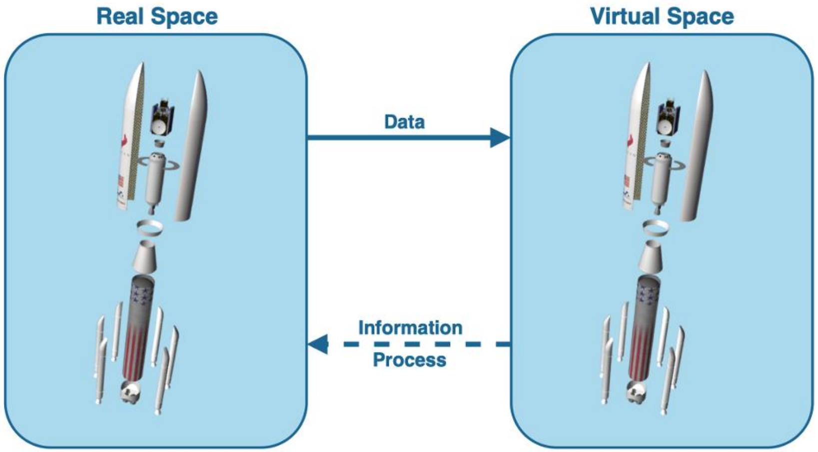
*"A **Digital Twin (DT)** is an executable virtual model of a physical thing or system." (Hughes, 2018)*

Key components (Grieves, 2014)

- Physical Object (PO) in the real space;
- Logical Object (LO, PO's digital counter part) in the virtual space;
- Data connection between the two of them.

Traditional **CAD** and advanced **IoT systems** fall short compared to real DTs:

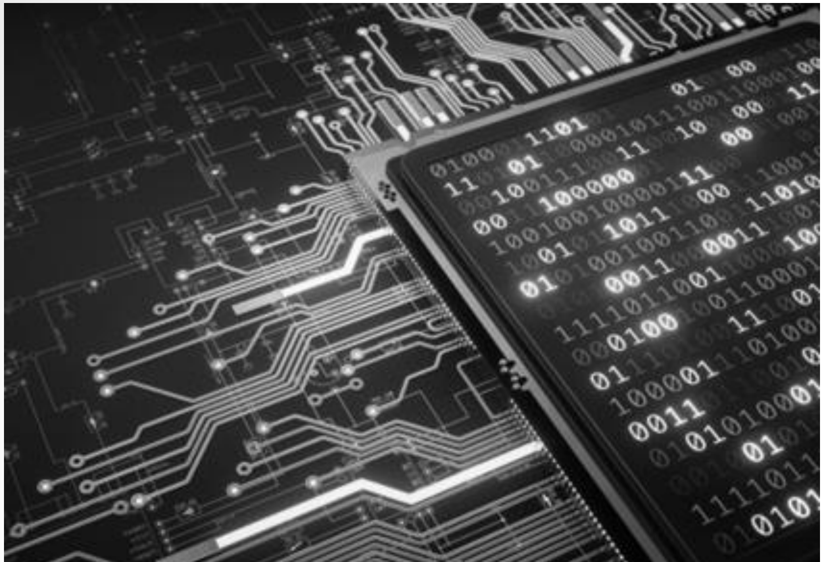
- CAD only exists in simulation worlds **and lacks interaction with real objects.**
- IoT systems **do not facilitate interaction between components** and the full process life cycles.



Information Mirroring Model proposed by Grieves

- Grieves, M. (2014). Digital twin: manufacturing excellence through virtual factory replication. White paper, 1(2014), 1-7.
- Hughes, A. (2018). Forging the digital twin in discrete manufacturing, a vision for unity in the virtual and real worlds. LNS Research e-book.

Towards Opportunistic Digital Twins



EI-powered DTs could "opportunistically" adapt to and act upon the physical environment that surrounds them. (Savaglio et al, 2023)

AI boosts DT beyond the "Digital Mirror," offering:

- **Adaptive Learning:** Actively learns and adapts to new data and evolving situations.
- **Pattern Detection:** Identifies anomalies for improved decision-making.
- **Predictive Maintenance:** Enables proactive optimization and efficiency.

Recent EI advancements unlock DT potential:

- **Simplify** complex environment representation and programming.
- **Enhance** real-time AI-based **inferences**, **data processing**, and **analysis**.
- Utilize AI for **advanced data generation**, surpassing traditional sensors.

*Savaglio, C., Barbuto, V., Awan, F. M., Minerva, R., Crespi, N., & Fortino, G. (2023). Opportunistic Digital Twin: an Edge Intelligence enabler for Smart City. *ACM Transactions on Sensor Networks*.

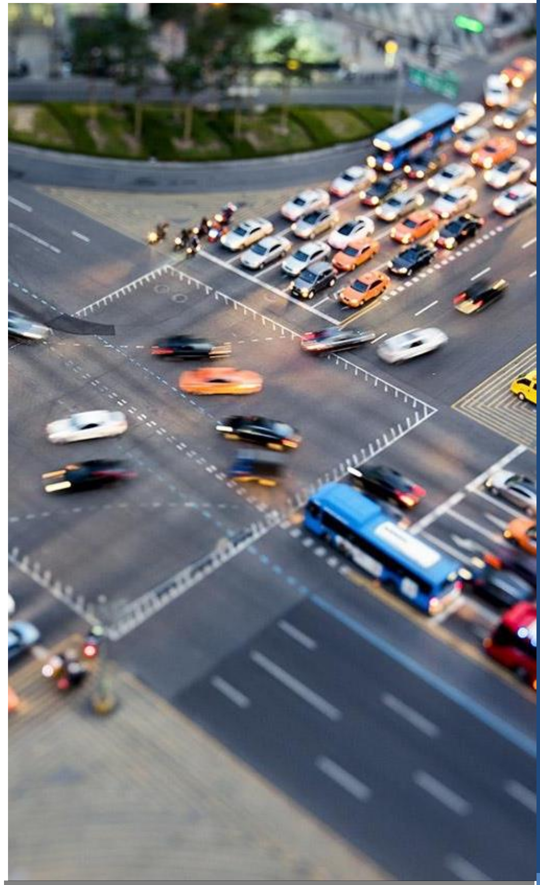
Use case:
EI-based Traffic Monitoring System (TMS)

Our vision

Revolutionize traffic monitoring with a cutting-edge TMS merging EI and the groundbreaking "opportunistic" DT concept.

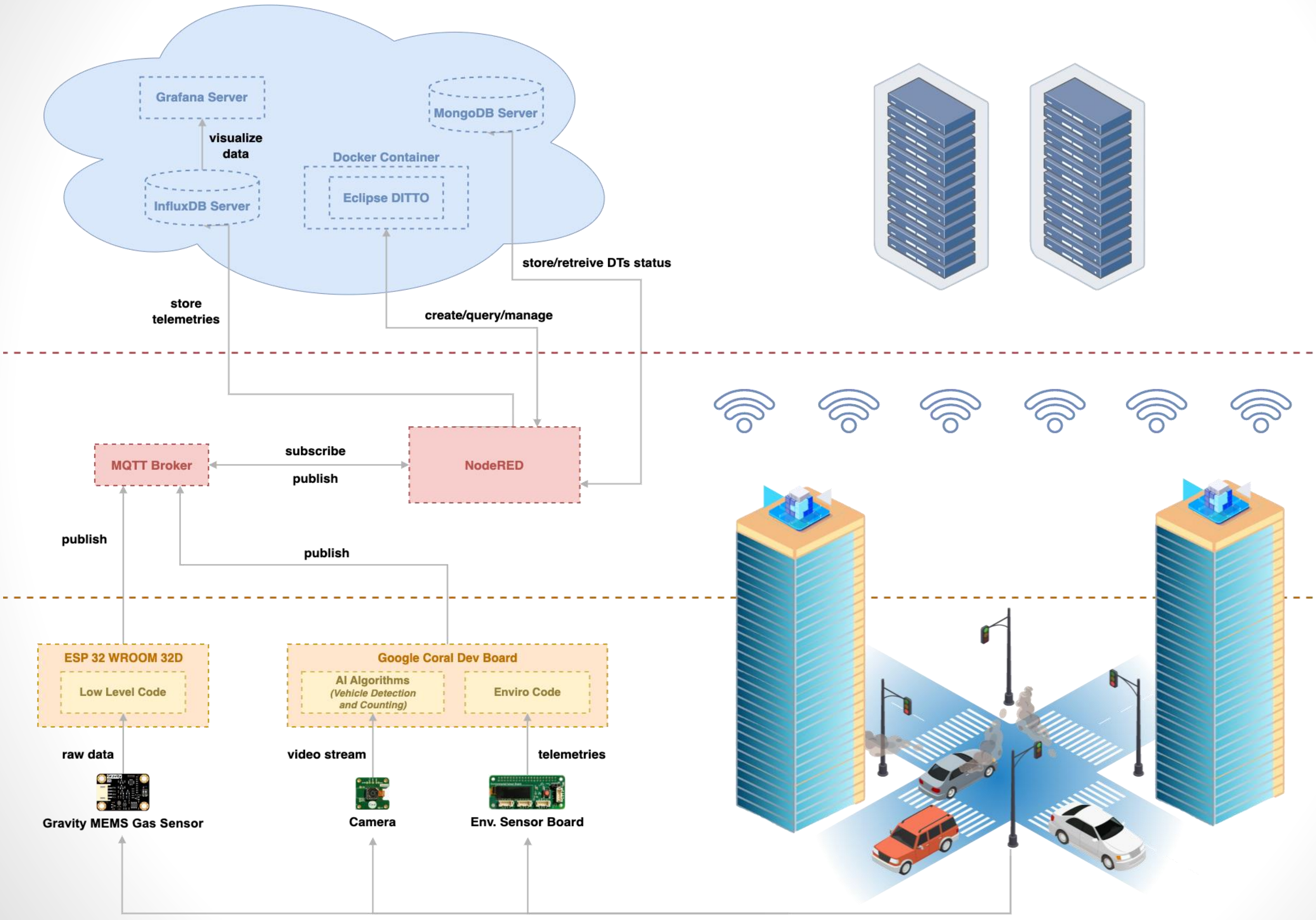
Key features

- **EI-based Technology:** AI at network edge slashes processing & transmission.
- **Synthetic Sensing over General-purpose Devices:** AI-enhanced board for diverse data, monitors hidden phenomena, boosts capabilities, cuts costs.
- **Data-driven and Bottom-up Approach:** Prioritizes data, builds from specifics, boosting monitoring accuracy.



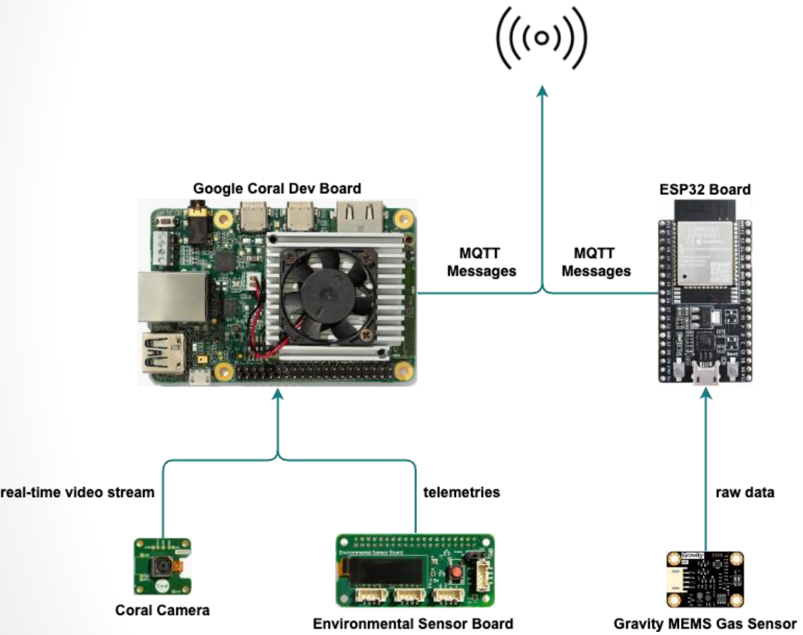
“ By 2030 almost 28% of the worldwide population will be concentrated in cities with at least 1 million inhabitants”

EI-Based Traffic monitoring system (TMS)



Use Case: Early Implementation

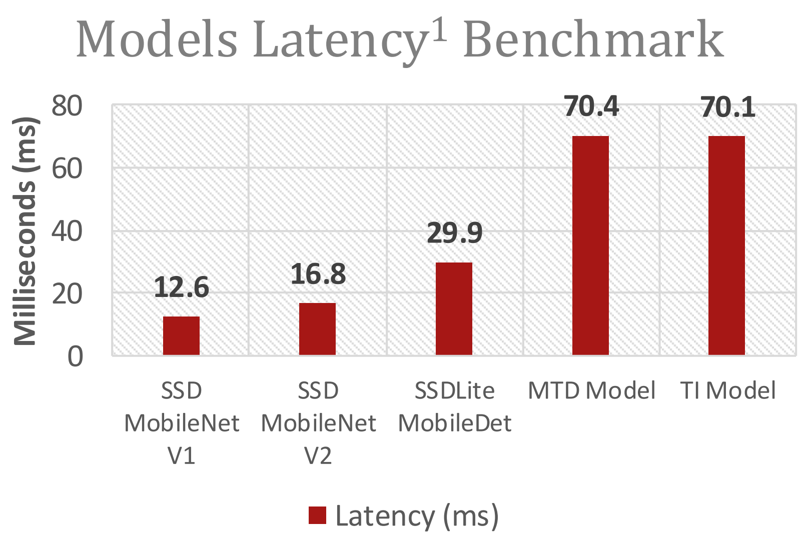
Hardware configuration

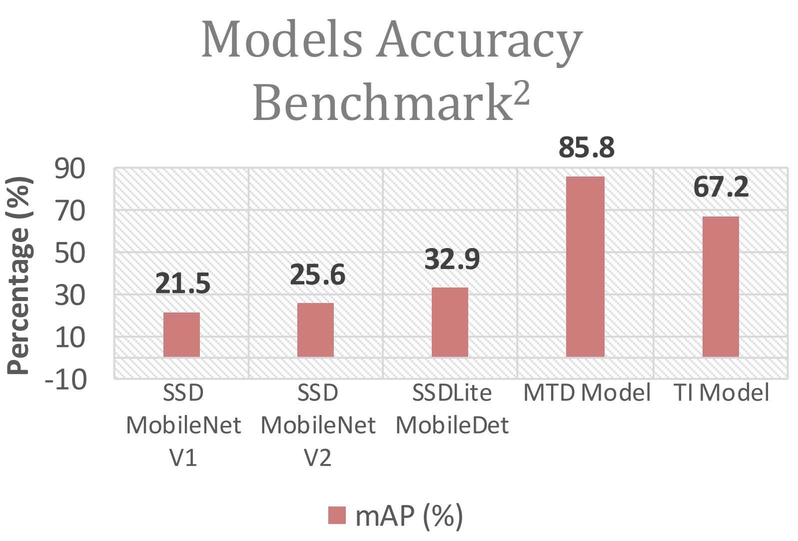


Software tools

Purpose	Technology	Layer
EI Framework	Tensorflow Lite[1]	Edge
Communication	MQTT[2]	Edge/Fog
Dispatching	Node-RED[3]	Fog
Telemetries Data Storage	InfluxDB[4]	Cloud
Data Visualization	Grafana[5]	Cloud
Virtualization through DT	Eclipse Ditto[6]	Cloud

Preliminary results: Accuracy and Latency for Vehicle Detection





- Pre-trained models (**SSD MobileNet V1, SSD MobileNet V2, SSDLite MobileDet**) demonstrate rapid inference but exhibit lower *mAP* values.
- Re-trained models (**MTD Model, TI Model**) achieve superior *mAP* scores while maintaining an acceptable inference time.

1. Latency is the time to perform one inference
2. Mean Average Precision (mAP) is the primary metric according to COCO evaluation metricsx

Preliminary results: Edge vs Cloud

We additionally performed a **comparative analysis** of TMS performance employing **two configurations**:

- **EI-based solution** using Google Coral Dev Board and Edge TPU
  - Vehicle detection on Coral Dev Board with Edge TPU
  - Transmitting inferences' output to system nodes
- **Cloud-centric solution** using real-time video frames
  - Capture video frames at edge
  - Transmit frames to Intel Core i7-6820HQ cloud instance
  - Process and transmit inference results to system nodes

	Edge	**Cloud**
Processor	Google Edge TPU coprocessor	Intel® Core™ i7-6820HQ, 2.70GHz x 8
Memory (RAM)	4 GB LPDDR4	32 GB
Graphics	Integrated GC7000 Lite Graphics	AMD® Bonaire/ Mesa Intel® HD Graphics 530

Hardware configurations: Edge- vs Cloud-based deployment

Preliminary results: Edge vs Cloud

Experiment Details

- Data traffic at the Edge:
  - Camera module captures video frames using Python algorithm
  - Each frame size: **~1,936 MB**
  - High data traffic leads to network latency (**~43ms** per frame)
  - Increased power consumption and bandwidth usage
- *One day interaction* between edge devices and server results in:
  - Transmitted frames: **1,729,000** (with a **20 fps**)
  - Data transmitted: **3.34TB**

Comparison

- Opting for an Edge-Centric solution over a Cloud-Centric approach:
  - Perform frame processing locally and transmit only the inference results
  - MQTT message size: just **67 bytes**, including the ID, payload, and control header.
  - Achieve a remarkable data traffic reduction of **10^4-fold**
  - Data transmitted: **0.872GB** instead of **3.34 TB**

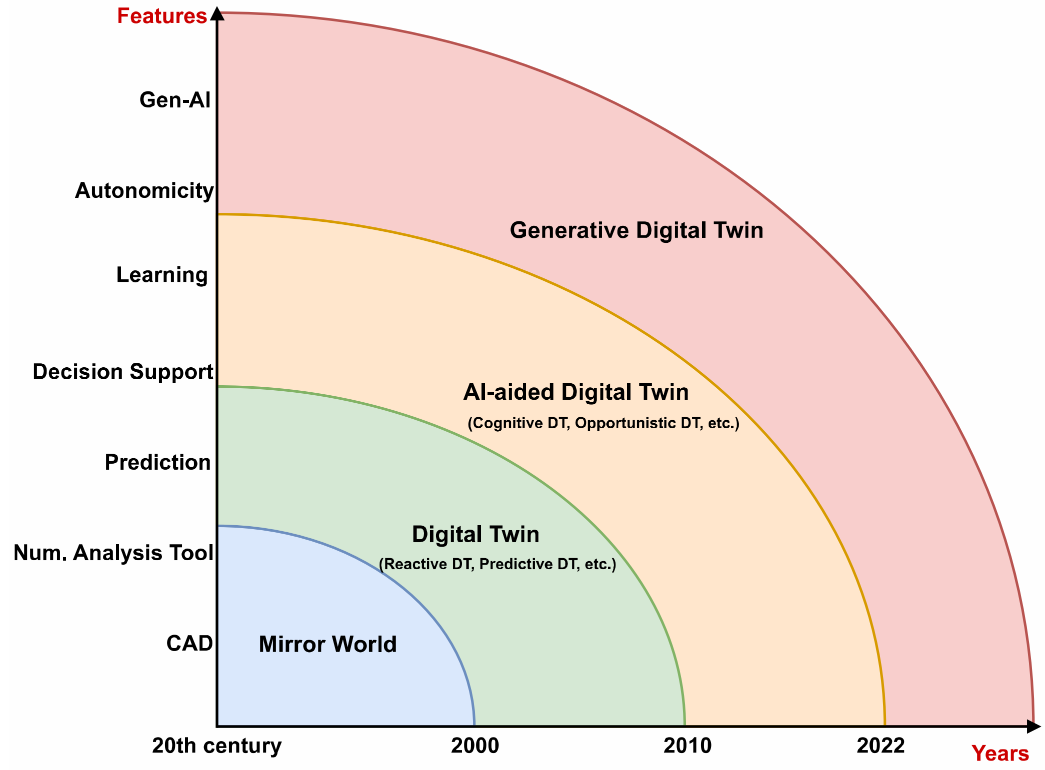
Moving computation rather than data effectively optimize data transmission and processing

Generative Digital Twins

Generative Digital Twin (GDT) is a novel approach which seamlessly merges classical DT model-driven systems with Gen-AI, creating a dynamically shaped system with exceptional adaptability.

Through the **generation of synthetic data** that faithfully replicates real-world scenarios, it elevates data quality surpassing conventional data augmentation methods, **facilitating smooth Human-DT and DT-DT interactions** in Augmented Reality (AR) and Virtual Reality (VR) environments.

Furthermore, the GDT's capacity to learn from real-time data distributions enhances simulation capabilities.



Generative Digital Twins:
Traditional Properties vs GDT Features

Properties	DT	GDT
Adaptability or Real-Time Modeling	Static and a priori defined with heavy computation effort [12]. Unsuitable for large-scale or complex real scenarios [5].	Dynamically shaped [13], customizes structure with background context changes [6], elevating simulation models.
Data Quality	Fed with error-prone real-time sensor data affected by environmental factors, wear, or calibration issues, causing data loss, noise, and inconsistencies.	Allows identifying faults in multiple sensors, advocating for error-free real-time data [6].
Data Generation and Augmentation	Dependence on low-precision and incomplete datasets collected from edge devices can significantly compromise the accuracy of any newly generated data [5].	Represents a source for generating new, close-to-real data, enhancing dataset quality and quantity [14].
Interaction with Physical Assets and Human Operators	Accessed through dashboards, often utilizing AR/VR for visualization.	Leverages on LLM to enhance Human-DT and DT-DT interactions, creating auto-generated AR/VR scenarios [2].
Simulation	Enables human-biased, event-driven simulations, often relying on ill-suited mathematical formulations [11].	Simulations become data-driven, with a more accurate representation using close-to-real data [11].

TABLE 2. Comparative Analysis of Traditional DT Properties and Improved Features in the proposed GDT.

Generative Digital Twins:
SOTA with different architectures

Ref. Paper	Gen-AI Contribution	Gen-AI technique	Application Scenario/Domain	Deployment considerations
[1]	Data-related	GAN	Healthcare, Energy, Manufacturing, Meteorology, Transportation, Cities and Education	Not given
[4]	Modeling-related	GPT series	Construction and Building industry	Not given
[5]	Data-related	cGAN, TS-GAN	Not given	Not given
[6]	Modeling-, Data-related	WGAN	WSN	Edge-Cloud framework (inferred)
[7]	Modeling-related	cGAN	Statistics	Not given
[8]	Modeling-, Data-, Simulation-related	GAN, VAE, CRBM	Healthcare	Cloud-based framework (inferred)
[9]	Modeling-, Data-related	HDFC-GAN	Industrial IoT	Cloud-based framework (inferred)
[10]	Data-, Interaction-related	LLMs, GANs, Trans-formers	Smart Agriculture	Not given
[11]	Modeling-, Simulation-related	WGAN	Industrial IoT	Cloud-based framework (inferred)
[12]	Modeling-, Simulation-related	C-DCGAN	Smart Manufacturing	Not given

TABLE 1. State-of-the-art analysis.

a) **Variational Autoencoders** (VAEs): learning complex data distributions and detecting anomalies
b) **Generative Adversarial Networks** (GANs): represent a model architecture tailored for training generative models, predominantly utilizing DL. They demonstrate remarkable proficiency in capturing and replicating intricate patterns that are inherent in physical systems.
c) **Transformers**, on which the so-called Large Language Models (LLMs): They have demonstrated remarkable capabilities in capturing contextual information and generating coherent sequences by learning statistical relationships from (not only) text documents during a computationally intensive self-supervised and semi-supervised training process.

Generative Digital Twins:

Deployment considerations: the need of continuum

The availability of data is a major issue for the DT definition, deployment, and execution: DT depends on data for monitoring and mirroring the twin status, environmental status, operation log and all of them can be collected and elaborated locally or remotely.

To conciliate benefits of Edge and Cloud Computing by alleviating their drawbacks, their synergic collaboration within the so-called Edge-Cloud continuum represent a solution able to manage the trade-off between latency and scalability, privacy and performance.

Already implemented in other domains, the concept of distributing the Gen-AI from Edge to Cloud can empower the potential of DTs in various applications within the IoT domain, but a thorough literature review exposes a significant disinterest.

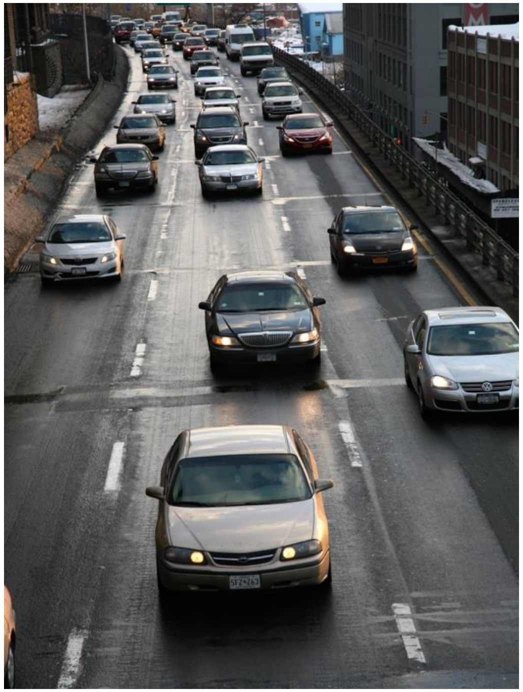
Indeed, as reported in Table 1, half of the works do not address the topic at all while the other seems adopting a pure Cloud-based deployment.

However, the spanning of Gen-AI systems across the Edge-Cloud continuum is, broadly speaking, a very overlooked aspect in the current literature.

Generative DT case Study:

A Generative AI-Driven Architecture for Intelligent Transportation Systems

LINK

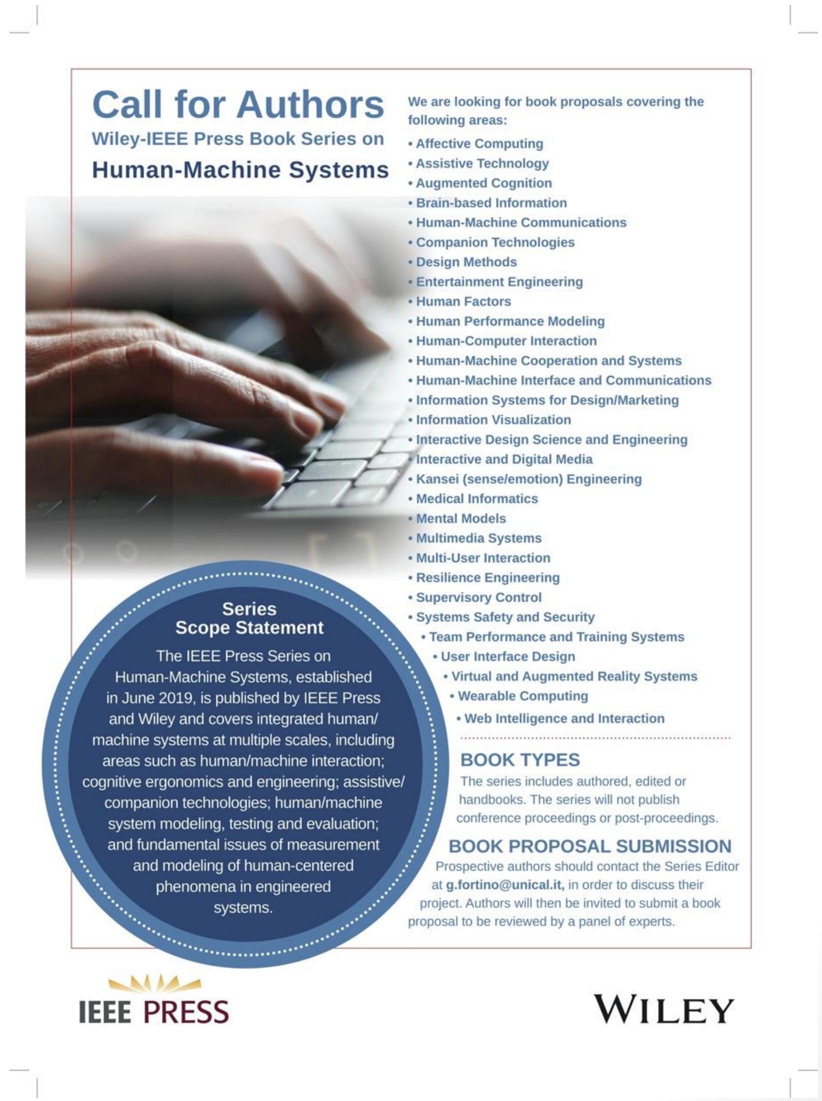


Final Remarks

- IoT-Edge-Cloud continuum is becoming a best practise!!!
- Pushing intelligence and machine learning to the IoT Edge is becoming a “must”!!!
- Towards autonomic systems based on the Integration of IoT-Edge-Cloud continuum with Opportunistic Digital Twins…
- Exploiting Generative DTs to leverage smart complex IoT scenarios… to be deployed onto the Edge-Cloud continuum
- *Trust & Security & Privacy… Another Talk…!!!*

Publication possibilities

- **Book Series**:



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