Real-time Machine Learning-based IoT Data Analysis in the Edge Cloud Continuum using AC^3

Jhofre Ojeda*, Dimitrios Amaxilatis§, Nikolaos Tsironis§, Themistoklis Sarantakos§,
João Fonseca*, Gereziher Adhane*, Golshan Famitafreshi*, Swastika Roy*, Shreya K. Chari*,
Navideh Ghafouri* Kostas Ramantas*, and Christos Verikoukis†‡

* *Iquadrat Informática, S.L.*, Barcelona, Spain
Email: {j.ojeda,j.fonseca,g.adhane,g.famitafreshi,s.roy,s.chari,n.ghafoori,kramantas}@iquadrat.com
† *University of Patras*, Patras, Greece
Email: cveri@ceid.upatras.gr
‡‡Industrial Systems Institute/Athena Research Center
§ *Spark Works Ltd.*, Galway, Ireland
Email: {d.amaxilatis,ntsironis,tsaradakos}@sparkworks.net

***Abstract*—The demo highlights how IoT data from Sensirion sensors and Raspberry Pis are processed using the Agile and Cognitive Cloud-edge Continuum Management (*AC*^{3}) framework. This approach optimizes data processing locations dynamically, balancing edge response and cloud computational power, enhancing real-time building management and smart city applications.**

***Index Terms*—cloud edge computing continuum, Internet of things, machine learning, data management, microservices**

I. Introduction

The rapidly growing Internet of Things (IoT) landscape has revolutionized data management, providing powerful solutions for monitoring and controlling systems at various levels. Denser sensor networks generates extensive data that unlock exciting new application possibilities.

However, unlocking the true value of this data deluge requires powerful processing and real-time analytics capabilities. To address this challenge, this work presents a novel approach based on the *AC*^{3} framework. We leverage the capabilities of the Cloud Edge Computing Continuum Manager (CECCM) to deploy and run microservices at the edge of monitored infrastructures. This allows real-time data processing using Artificial Intelligence (AI), enabling instant decisions and automated responses based on current conditions. Furthermore, the demo leverages *AC*^{3} components to demonstrate seamless microservice migration across the CECC infrastructure. Combined with zero-touch configuration and application management, it streamlines the data life-cycle, potentially accelerating application development and deployment across the cloud-edge continuum.

II. Related Work

Several studies explored real-time data processing in the context of IoT. Catalfamo et al. [1] proposed a Cloud-Edge machine learning solution for a hydrogeological use case. Additional studies [2]–[4] explored integrating deep learning for various IoT applications at the edge, including wearable devices and speech recognition, to improve audio recognition accuracy. These works, like ours, investigate frameworks that distribute computational tasks between edge devices and the cloud to optimize response times and resource usage. Our work builds upon these efforts and introduces *AC*^{3} framework, which dynamically determines the optimal location for data processing based on factors such as real-time response needs and computational complexity.

This work is supported by the European Union's Horizon Program under the Agile and Cognitive Cloud edge Continuum management (AC3) project (Grant No. 101093129).

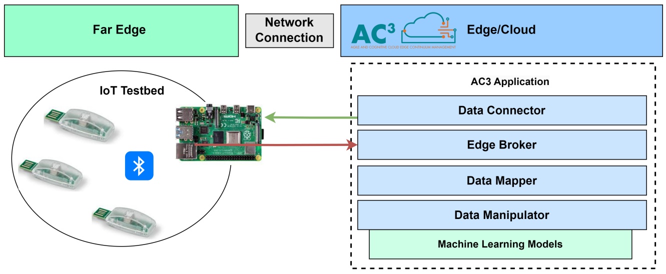

Fig. 1. Architecture of the demo

III. Implementation

The demo emphasizes the novel CECCM framework, an *AC*^{3} vital component that leverages AI, ML, and semantic context-awareness algorithms to predict events, and manage application life cycle, and IT resources. Furthermore, the framework ensures it operates as a cognitive system on top of a cloud-edge continuum architecture, seamlessly integrating with real-time data sources.(Fig. 1).

A. IoT Layer Setup

At the heart of the demo is the the IoT layer, equipped with Sensirion sensors strategically placed throughout the Iquadrat office building to provide a real-time granular view of environmental conditions. They measure the following

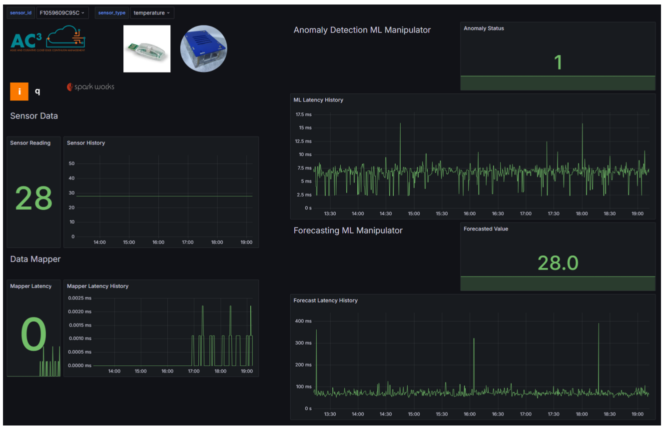

Fig. 2. Dashboard showcasing the raw and processed data flow.

`environmental variables`: CO_2 concentration, temperature, and relative humidity.These variables are ideal for ensuring the health and comfort of the users at the office. Raspberry Pis serves as far-edge devices to collect and transmit data to processing layers.

B. Key Components of the AC3 Data Management System

The AC3 Data Management System includes the Data Connector, the Data Mapper, and the Data Manipulator.

The **Data Connector** is the first touchpoint in the data management chain. It communicates directly with the far-edge devices, retrieves the environmental data, and initiates its journey through the AC^3 ecosystem to ensure it is promptly forwarded to the subsequent stages for further processing. According to Hedge and S. [5], RabbitMQ guarantees message delivery and provides a more versatile approach compared to Apache Kafka and Redis. RabbitMQ is selected as the **Message Broker**, to efficiently manage data transfer from the far edge to processing locations, whether at the edge or in the cloud.

Upon environmental data arrival at the edge or cloud processing centers, the **Data Mapper** takes over the work. This component converts the incoming data into a standardized format that downstream applications can easily use, e.g., the Data Manipulator. Standardized data ensures seamless application interaction within the AC^3 ecosystem, eliminating the need for custom adapters.

The **Data Manipulator** uses the Isolation Forest and TensorFlow ML models to identify patterns and potential anomalies in standardized environmental data. This enables real-time anomaly detection and forecasting to enhance building safety and operational efficiency. ML models were evaluated using real-world and synthetic data to ensure distribution and robustness.

IV. Demonstration

The main output of our demo is an Interactive Grafana[1] dashboard showing the AC^3 system's data journey and analytics in real-time, composed of two dashboards. All the Grafana dashboards need to be accessible through a web browser with an internet connection to provide real-time insights into the system's performance.

The main dashboard Fig. 2 serves as the focal point for observing the raw data flow and its subsequent processing, in specific it shows:

- `Real-time` and `historical data` of environmental variables from the Sensirion sensors are displayed.
- `Data Mapping latency` is monitored to evaluate processing efficiency in real-time.
- The `environmental anomalies scores` and associated **historical processing times** in computation.
- The `Predicted environmental conditions` and associated `processing times`.
- The computational efficiency and predictive power of the system.

The second dashboard focuses on the operational aspects of the RabbitMQ message broker. This dashboard includes: real-time data on the number of messages processed per second by RabbitMQ, highlighting the throughput and efficiency of the data transfer system. It also details on the number of active connections to the RabbitMQ broker, alongside metrics on Consumer, Publishers and Nodes, helping to assess the system's load and resource utilization.

V. Conclusion

This demo showcases the capabilities of the AC^3 framework for real-time processing and analysis of IoT data. CECCM, a key framework component, dynamically distributes processing tasks between the edge for lower latency and the cloud for intensive tasks. This empowers real-time operational optimizations. The demo also highlights AC^3's robust data management and analytics capabilities. It demonstrates applicability in real-world situations, particularly for improving comfort and building management in smart cities. Our demo summarizes the proactive decision-making and system optimization capabilities of the AC^3 project in managing IoT environments and reinforcing its applicability in real-world smart cities scenarios.

References

[1] A. Catalfamo, A. Aral, I. Brandic, E. Deelman, and M. Villari, "Machine learning workflows in the computing continuum for environmental monitoring," in *International Conference on Computational Science*, pp. 368–382, Springer, 2024.

[2] H. Li, K. Ota, and M. Dong, "Learning iot in edge: Deep learning for the internet of things with edge computing," *IEEE network*, vol. 32, no. 1, pp. 96–101, 2018.

[3] S. Bhattacharya and N. D. Lane, "Sparsification and separation of deep learning layers for constrained resource inference on wearables," in *Proceedings of the 14th ACM Conference on Embedded Network Sensor Systems CD-ROM*, pp. 176–189, 2016.

[4] M. A. Alsheikh, D. Niyato, S. Lin, H.-P. Tan, and Z. Han, "Mobile big data analytics using deep learning and apache spark," *IEEE network*, vol. 30, no. 3, pp. 22–29, 2016.

[5] R. G. Hegde, "Low latency message brokers," in *International Research Journal of Engineering and Technology (IRJET)*, 2020.

[1]https://grafana.com/