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L. Ferrigno, L. Milano, M. Molinara, H. Mustafa, A. Miele
Dept. of Electrical and Information Engineering
University of Cassino and Southern Lazio
Cassino, Italy
{ferrigno; filippo.milano; m.molinara; hamza.mustafa, alessio.miele}@unicas.it

Michele Vitelli
Sensichips srl
Aprilia, Italy
michele.vitelli@sensichips.com

***Abstract*—Artificial Intelligence (AI) is transforming industries, particularly through Industry 4.0, by integrating technologies such as the Internet of Things (IoT) to optimize production processes and resource management. It addresses challenges such as reducing environmental impact while fulfilling consumer demands. Innovative sensors enable real-time data collection for environmental monitoring. This paper presents three experiences suitable for applying machine learning in smart cities for sensor data interpretation: air and water pollutant detection and state of charge estimation of Li-Ion batteries.**

***Index Terms*—Artificial Intelligence, Industry 4.0, Smart Sensors, Pollutants Identification, State of Charge estimation**

I. Introduction

Artificial Intelligence (AI) transforms sectors like healthcare, finance, education, transportation, and industry by analyzing vast data sets in real-time and generating precise predictive insights. Industry 4.0 marks a pivotal shift in industrial evolution, emphasizing "smart factories" where machines, systems, and people are interconnected via IoT, AI, big data, cloud computing, and advanced robotics.

Industry 4.0's [1] automated and connected production optimizes processes through real-time machine communication. Innovative sensors are key in collecting detailed, real-time environmental and operational data. AI analysis of sensor data benefits industries by identifying pollutants, monitoring air and water quality, and optimizing processes to reduce environmental impacts.

In the automotive sector, the shift towards sustainable mobility is driven by energy cells, especially lithium-ion batteries, which are crucial for zero-emission vehicles. Understanding parameters like range, energy density, charging time, and durability is vital for developing large-scale zero-emission vehicles and ensuring proper disposal and reuse.

Upcoming sections discuss Machine Learning (ML) applications in industrial challenges, focusing on detecting air and water pollutants and estimating the State of Charge in automotive applications [2]–[4].

II. Pollutant identification in Air

Our recent study presents a novel system combining sensor technology and machine learning to detect and classify air contaminants affordably and effectively. Existing solutions face challenges in size, cost, and complexity. Our system addresses these issues using a sensor array that includes aluminum oxide for VOC detection, a commercial capacitive humidity sensor, and a graphene-functionalized sensor for pollutant sensitivity.

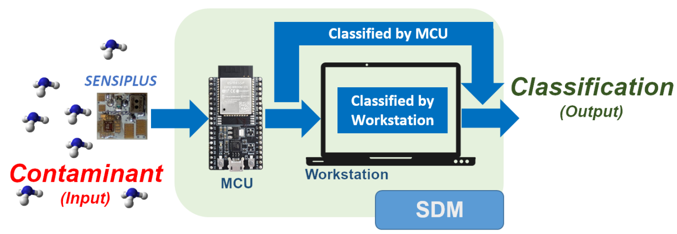

Fig. 1. The proposed integrated system. SDM stands for SENSIPLUS Deep Machine.

The system integrates with the SENSIPLUS platform for precise electrical impedance measurements. Key components include the SENSIPLUS Chip (SPC), developed by Sensichips s.r.l. and the University of Pisa, and the SENSIPLUS Deep Machine (SDM) for data acquisition and analysis. Machine learning models like MLP, CNN, and LSTM were trained on sensor data to classify contaminants with over 75% accuracy, although some substances like acetone and alcohol were more challenging to distinguish [5].

Our methodology simulated indoor air conditions to generate comprehensive sensor data. The system optimizes low-power operations suitable for IoT applications, ensuring practical deployment. Future enhancements include integrating more sensor types, exploring advanced ML models, and developing real-time monitoring capabilities. Our study highlights the potential and challenges of sensor-based, AI-integrated air quality monitoring systems, contributing to more accessible and accurate environmental monitoring solutions.

III. Pollutant identification in Water

Detecting illegal pollutants in wastewater is crucial for public health. We propose an IoT-ready node for sensing, processing, and transmitting wastewater pollutant data using the Smart Cable Water (SCW) system with SENSIPLUS chip sensors. The system employs impedance spectroscopy for pollutant detection and machine learning for data processing on a low-cost Micro Control Unit, enhancing anomaly detection and classification accuracy.

The SCW system, developed by Sensichips s.r.l., uses InterDigitated Electrodes (IDEs) coated with various metals

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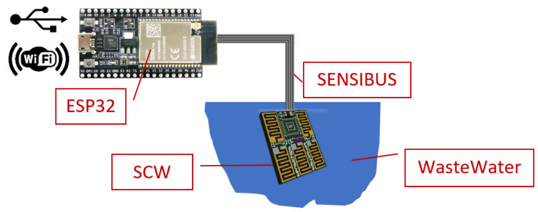

Fig. 2. Identification system architecture.

to detect pollutants in Synthetic WasteWater (SWW), which simulates real sewage conditions. Fourteen substances were tested and divided into target pollutants and outliers. Sensor data, including resistance and capacitance measurements, is preprocessed and analyzed through a Finite State Machine (FSM) to ensure accurate classification.

The classification process involves two phases: data preprocessing and classification. Preprocessing normalizes sensor data and establishes a baseline, while the classification phase uses anomaly detection and optimized KNN models to identify substances. Combining anomaly detection with a multiclass classifier improved accuracy, achieving a 79.4% success rate in identifying pollutants, though some outliers like sodium hypochlorite were misclassified [6].

IV. Optimization of Battery State of Charge Estimation

Accurately monitoring the State of Charge (SoC) is essential for estimating battery life and controlling temperature. Traditional methods like Coulomb counting and Open Circuit Voltage (OCV) face challenges such as measurement inaccuracies, especially in battery types like Lithium Iron Phosphate (LFP) where the voltage-SOC relationship is flat. Electrochemical Impedance Spectroscopy (EIS) offers promise but has long measurement times. This study proposes a method to reduce measurement time while ensuring precise SoC estimation, focusing on EIS and knowledge-based SoC classification.

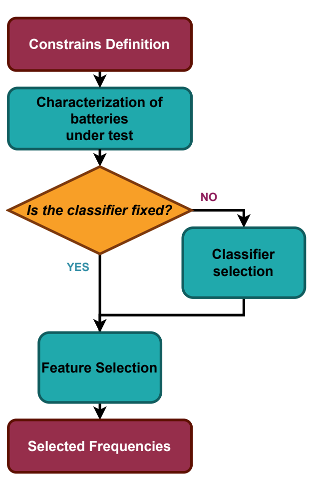

Fig. 3. The proposed method workflow.

The approach involves several steps depicted in Figure 1. First, design parameters and constraints are identified, including SoC estimation resolution, target measurement time, accuracy goals, battery type, and classifier selection. The device under test is then characterized to meet stringent performance parameters. A classifier is chosen based on accuracy metrics and integrated into a feature selection algorithm. The final stage optimizes feature selection using search algorithms to minimize measurement time while maintaining accuracy above specified targets.

In this work, SoC estimation is approached with 10-class classification models, each representing a 10% interval of SoC. Data includes impedance features (28 parameters across real and imaginary parts at various frequencies) from Nyquist plots of battery cells at different SoCs. Optimization algorithms, specifically Particle Swarm Optimization (PSO), identify optimal frequencies for impedance measurement via EIS, balancing accuracy and measurement time using a supervised learning model. This case study demonstrates a systematic approach to enhancing SoC estimation efficiency using EIS and structured optimization techniques, which are crucial for advancing battery management technologies [7].

V. Acknowledgement

The EU partially supported this work in the NextGenerationEU plan through MUR Decree n. 1051 23.06.2022 ”PNRR Missione 4 Componente 2 Investimento 1.5” - CUP H33C22000420001, partially through Horizon Europe RHEMEDiation with (GA 101113045).

References

[1] R. S. Peres, X. Jia, J. Lee, K. Sun, A. W. Colombo and J. Barata, ”Industrial Artificial Intelligence in Industry 4.0 - Systematic Review, Challenges and Outlook,” in IEEE Access, vol. 8, pp. 220121-220139, 2020, doi: 10.1109/ACCESS.2020.3042874.

[2] J. Zhang and D. Tao, ”Empowering Things With Intelligence: A Survey of the Progress, Challenges, and Opportunities in Artificial Intelligence of Things,” in IEEE Internet of Things Journal, vol. 8, no. 10, pp. 7789-7817, 15 May15, 2021, doi: 10.1109/JIOT.2020.3039359.

[3] B. Assiya, T. Agouti, J. Zahir, A. Ait-Mlouk and M. E. Adnani, ”Big data and Intelligent decision Making: Approaches and Applications,” 2022 16th International Conference on Signal-Image Technology Internet-Based Systems (SITIS), Dijon, France, 2022, pp. i-viii, doi: 10.1109/SITIS57111.2022.00074.

[4] F. Sherwani, M. M. Asad and B. S. K. K. Ibrahim, ”Collaborative Robots and Industrial Revolution 4.0 (IR 4.0),” 2020 International Conference on Emerging Trends in Smart Technologies (ICETST), Karachi, Pakistan, 2020, pp. 1-5, doi: 10.1109/ICETST49965.2020.9080724.

[5] M. Molinara, M. Ferdinandi, G. Cerro, L. Ferrigno and E. Massera, ”An End to End Indoor Air Monitoring System Based on Machine Learning and SENSIPLUS Platform,” in IEEE Access, vol. 8, pp. 72204-72215, 2020, doi: 10.1109/ACCESS.2020.2987756.

[6] L. Gerevini, G. Cerro, A. Bria, C. Marrocco, L. Ferrigno, M. Vitelli, A. Ria, M. Molinara, An end-to-end real-time pollutants spilling recognition in wastewater based on the IoT-ready SENSIPLUS platform, Journal of King Saud University - Computer and Information Sciences, Volume 35, Issue 1, 2023, Pages 499-513, ISSN 1319-1578,

[7] C. Bourelly, M. Vitelli, F. Milano, M. Molinara, F. Fontanella and L. Ferrigno, ”EIS-Based SoC Estimation: A Novel Measurement Method for Optimizing Accuracy and Measurement Time,” in IEEE Access, vol. 11, pp. 91472-91484, 2023, doi: 10.1109/ACCESS.2023.3308029.