Using Nanomaterials and Machine Learning for Advanced Sensing Applications

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1. Nanomaterials and deep transfer learning for improved sensing platforms

Reliable real-time monitoring pollutants is a major need in industrial and residential areas, to ensure health and safety [1]. Traditional techniques, such as chromatography [2], are not suitable for a real time in-situ detection, hence effort is currently addressed to assess monitoring and sensing technologies suitable for: i) in-situ monitoring (through compact sensing platforms); ii) smart distributed systems (collective data processing).

The first concept is addressed through alternative electrical and electrochemical techniques, such as Voltammetry, VA [3-4] or Electrical Impedance Spectroscopy, EIS [5-7]. Indeed, both techniques can be implemented by means of compact systems with hand-held sensing platforms connected to portable instrumentation. For instance, disposable Screen-Printed Electrodes (SPEs) can be used as sensing platforms. However, the limits of conventional SPEs (i.e., made by graphite, carbon, etc.) related to their sluggish surface kinetics severely affect the sensor performance indicators (such as sensitivity, selectivity, responsivity, etc.. [4]).

To overcome these limits, the SPEs can be modified by enhanced materials, such as the promising Carbon Nano-Materials (CNMs), that can improve surface kinetics and enhance electroactive surface area [4-5]. More in general, CNMs are abundant and span a wide range of physical and chemical properties that can be tailored according to the purposes. Graphene, Carbon Nanotubes (CNTs), Nano-Diamond (ND) and their derivates have been widely employed for electrochemical sensing in recent years [8-9].

Despite the high improvement in SPEs' performance after their modification, a reliable technology for in-situ real-time monitoring based on these platforms and the above-mentioned techniques is still far to be assessed. Indeed, major limits still need to be overcome: (i) high sensitivity of the platforms to uncertainties of the fabrication process, environmental conditions, and ageing effects; (ii) complicated time- and resource-consuming calibration procedures, needed for in-situ measurements; (iii) difficult classification of substances with similar electrical and electrochemical footprint.

Many of the above issues can be faced by moving from conventional solutions to IoT paradigms [10]. This is the second concept mentioned above: the sensing platforms becomes nodes of a smart distributed sensing system, where the data are processed both locally and collectively (e.g., in Cloud), eventually by means of Artificial Intelligence (AI) algorithms. This approach can strongly improve the monitoring performance also in presence of the above-mentioned uncertainties, see for instance [11], where IoT-based real-time frameworks are proposed to perform water quality monitoring, by using machine learning approaches and cloud computing.

The talk will present some recent results related to the detection and classification of organic pollutants (quinones) in water performed by means of EIS and VA techniques. Improved sensing platforms will be shown, where the sensing membranes for EIS and working electrodes for VA are modified by means of 2D nanomaterials. Examples of AI-based post-process will be also discussed, with the possibility of classifying the pollutants starting from VA results, transformed into equivalent images via GAF transformations and finally processed by pre-trained convolutional neural networks.

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3. References

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