Sensor– and machine learning–based insights into indoor atmospheric corrosion

Haijie Tong,[1] Erickf Yuen,[2] Gengfu He,[2] Guohui Zhong,[2] Pin Zhang,[3] Sviatlana Lamaka,[1] Mikhail Zheludkevich[1]

1. Electrochemistry and Big Data Department, Institute of Surface Science, Helmholtz-Zentrum Hereon, Max-Planck-Str. 1, 21502 Geesthacht, Germany.
2. Department of Civil and Environmental Engineering, The Hong Kong Polytechnic University, Hung Hom, Kowloon 999077, Hong Kong, China
3. Department of Engineering, University of Cambridge, United Kingdom

Helmholtz-Zentrum hereon

Institute of Surface Science

Abstract

Human beings averagely spend more than 90% of time in indoor environments. Indoor anthropogenic emissions cause serious metallic corrosion and lead to huge economic cost. However, the mechanism of indoor metallic corrosion has not been well understood, which is largely due to the lack of high time-resolution monitoring instruments and advanced data processing tools. To tackle this challenge, we employed atmospheric corrosion monitoring (ACM) sensors, portable indoor air quality monitoring systems, and machine learning techniques to study the corrosion of steel and zinc in a student canteen in The Hong Kong Polytechnic University. The ACM sensors allow us to track the galvanic corrosion process between silver and steel or zinc at second time-resolution. Portable instruments enable us to obtain the real-time concentrations of temperature, relative humidity, fine particulate matter, and carbon dioxide. Random forest model was used to estimate the impacts of local environmental conditions on corrosion rate. We found the corrosion current above average heavily relied on surface contamination by cleaning- or cooking-generated droplets, whereas the corrosion current below average is mainly driven by atmospheric corrosion.

Fig. 1. Research site: student canteen in The Hong Kong Polytechnic University. Environmental characteristics of this area: high temperature, high humidity, and frequent cooking and cleaning activities.

Fig. 2. Image of metallic corrosion: sunbstantial amounts of rust formed on the surface of metallic cooking cabinet in the target kitchen (Fig. 1).

Research Methods

Fig. 3. Research tools used in this study. ACM sensor is used for testing corrosion current.[1] Q-Trak is used for testing the concentration of CO_2. DUSTTRAK II is used for testing the concentration of $PM_{2.5}$. RF model is used for data processing and analysis.

Results

We found that cooking and cleaning activities induced deposition of liquid droplets on ACM sensor surface, which accelerated corrosion (Fig. 4). The corrosion current peaks exhibit substantial overlapping with the environmental factors (Fig. 5), reflecting the strong effects of atmospheric corrosion. RF-based modeling indicates that separation of corrosion current to above average and below average can significantly improve the model performance towards all the data (Fig. 6). The corrosion current above the average corresponds to the deposition of cleaning- or cooking-generated droplets (Figs. 4 and 5). The corrosion current below average can be described by local environmental conditions (RH, T, CO_2, and $PM_{2.5}$), reflecting the plausible driven effect of atmospheric corrosion (Fig. 6c and 6f).[2] RF-based importance index analysis indicates that RH, T, CO_2, and $PM_{2.5}$ exhibit decreasing impacts to the corrosion of steel and zinc in the targeted canteen environment (Fig. 7).[3] RH exhibits a stronger role to the steel corrosion than to zinc corrosion, reflecting their different corrosion process as well as a plausible more hygroscopic surface of Steel/Ag sensor or the deposited contaminants.

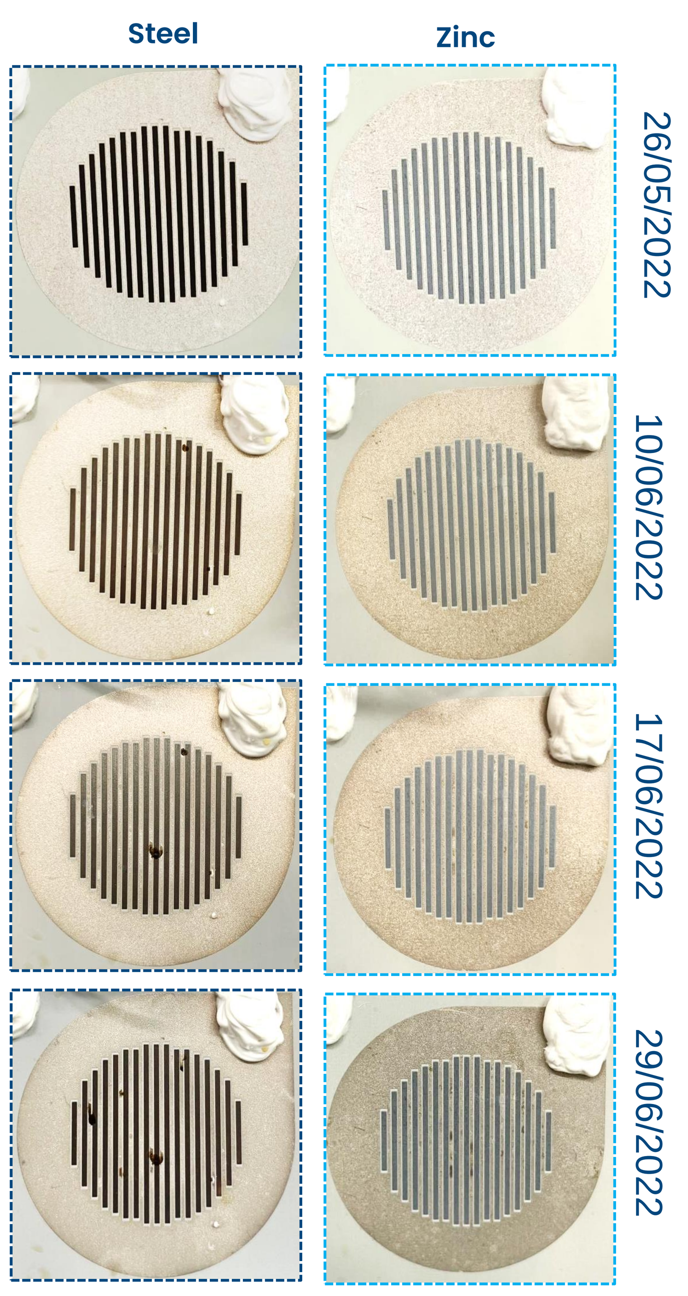

Fig. 4. Images of ACM sensors during the corrosion process. Left column: Steel/Ag sensor. Right column: Zinc/Ag sensor.

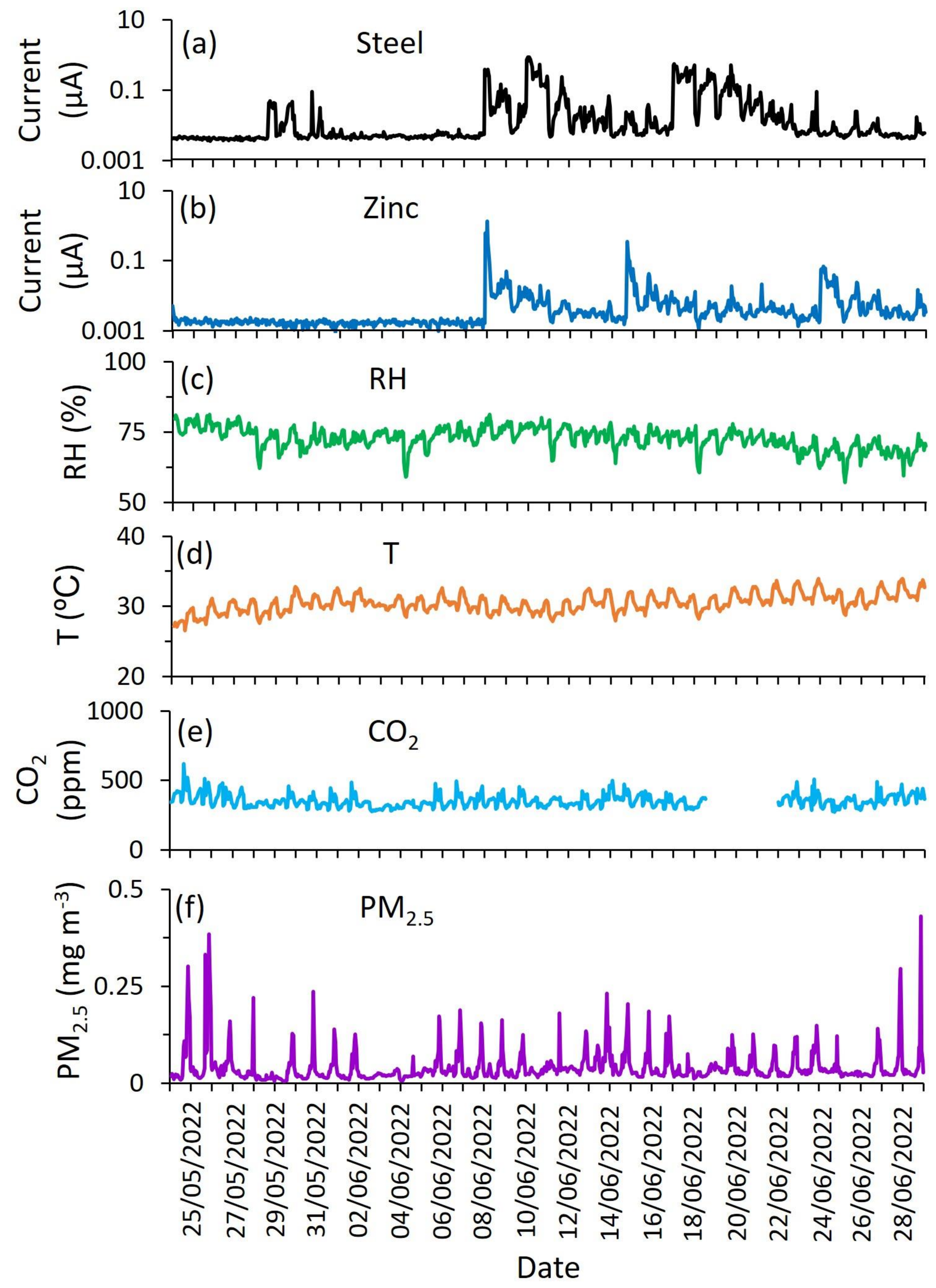

Fig. 5. Corrosion current (a-b) and environmental factors (c-f) measured at the research site. (a) Steel/Ag sensor. (b) Zinc/Ag sensor. (c) Relative humidity (RH). (d) Temperature (T). (e) Carbon dioxide. (f) Fine particulate matter.

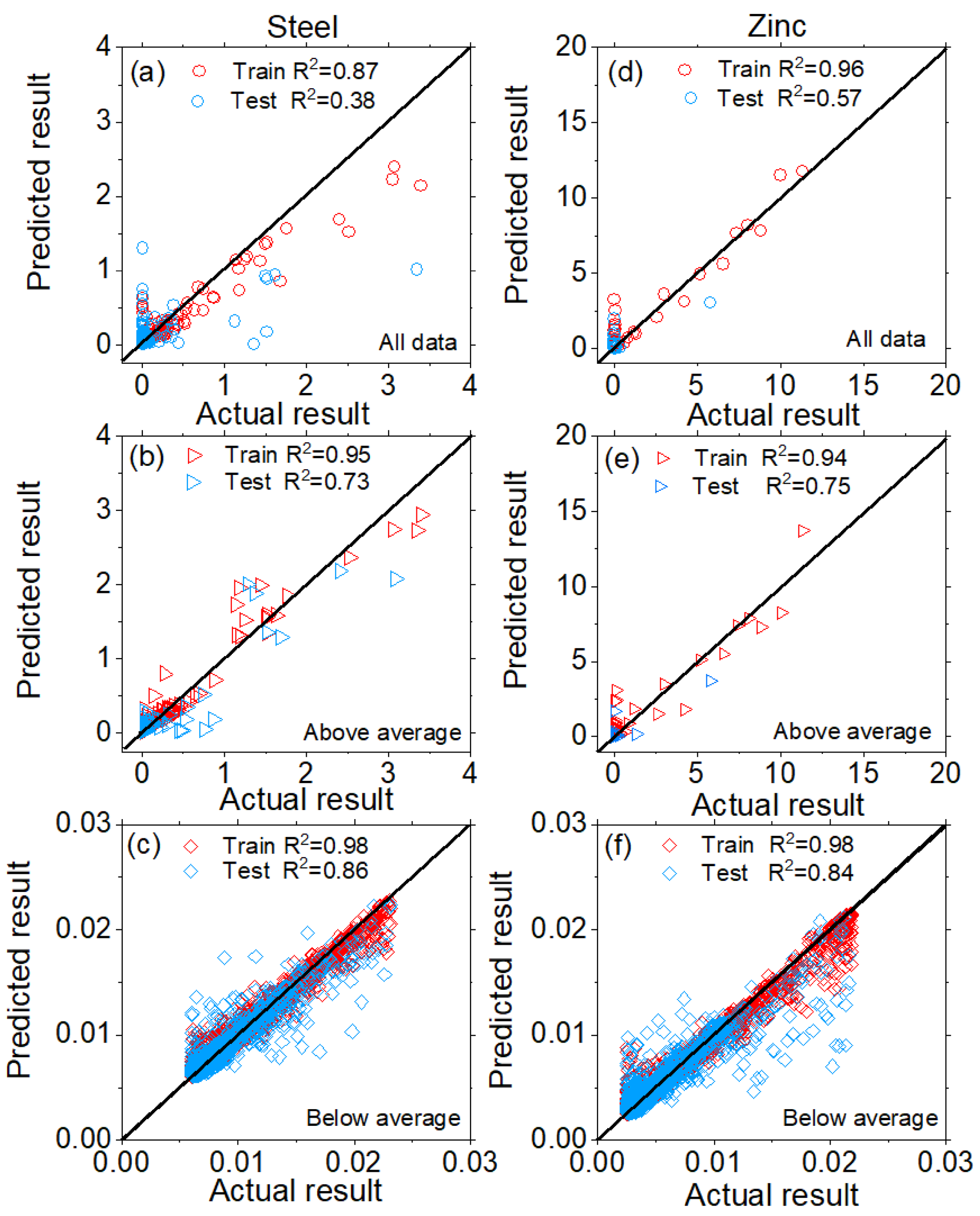

Fig. 6. RF-based fitting results for the training (red points) or testing (blue points) samples of steel (a-c) or zinc (b-f). (a, d) All data. (b, e) Results for corrosion current above the average of all data. (c-f) Results for corrosion current below the average of all data.

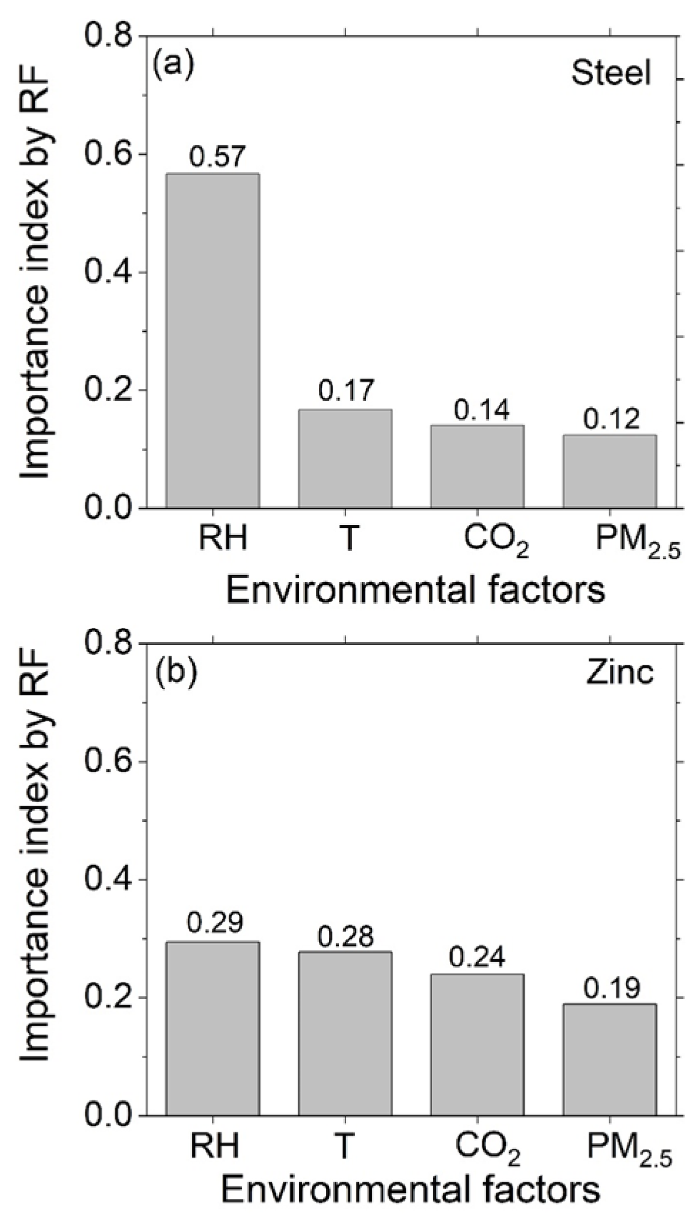

Fig. 7. Importance index of environmental factors to corrosion current below average. (a) Steel/Ag sensor. (b) Zinc/Ag sensor.

Reference

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Helmholtz-Zentrum **Hereon** • Max-Planck-Straße 1 • 21502 Geesthacht I Germany • www.hereon.de
Contact: Dr. Haijie Tong • T +49 4152 87-2185 • M +49 1626632600 • haijie.tong@hereon.de