

Original article

Cross-Disciplinary Optimization of Autonomous Environmental Monitoring Systems: Integrating Electrochemical Sensing and Low-Power Electronics via Pearson-RSM-NSGA-II Frameworks

Abdelgader Alsalhin^{1,2}, Khalefa Faneer^{1*}, Hamza Al-Bukhari³¹Florida Institution of Technology Melbourne Florida, USA²High Institute of Science and Technology, Bent Baya, Wadi AlAjaj, Libya³Department of Computer Networks, Faculty of Information Technology, Al-Margib University, Al-Khoms, LibyaCorresponding Email. kfaneer@gmail.com

Abstract

The Great Man-Made River (GMMR) constitutes a vital 4,000-km network of prestressed concrete cylinder pipes (PCCP) essential for Libya's water security. Despite its scale, the infrastructure faces catastrophic failures driven by chloride-induced corrosion of prestressed wires within aggressive Saharan soil. This study proposes a novel "Integrated Cognitive Pipeline" architecture that employs Response Surface Methodology (RSM) as a high-fidelity surrogate modeling engine to ensure long-term structural integrity. The novelty of this approach lies in its ability to resolve interdisciplinary conflicts between Chemical Engineering goals, such as maximizing cathodic protection effectiveness, and Electrical Engineering constraints, including sensor battery depletion and electromagnetic signal interference in RF-harsh desert environments. By optimizing a multidimensional design space—where input factors like geometrical IDE gap width, sampling frequency, and CP excitation voltage are mapped against responses such as polarization resistance (R_p) and signal-to-noise ratio—the framework delivers a Pareto-optimal sensor deployment strategy. Integrating RSM with Bayesian multi-rate sensor fusion allows the system to supplement physical acoustic emission (AE) hits with "soft sensor" environmental data, enabling predictive maintenance. This cognitive decision-making loop significantly reduces the logistical burden of physical inspections in remote desert regions. Beyond technical efficiency, this optimization serves as a critical sustainability intervention within the "Water-Energy-Food Nexus" framework. By achieving an estimated 10% reduction in water loss and pumping energy, the RSM-optimized system safeguards the finite Nubian Sandstone Aquifer, demonstrating that the "Integration of Sciences" is the only viable path to securing complex infrastructure resilience in the 21st century.

Keywords. Corrosion Pipeline, Electrical Engineering, Chemical Engineering, RSM, Integration of Science.

Introduction

The sustainable management of large-scale infrastructure in arid regions is inextricably linked to the global Water-Energy-Food (WEF) Nexus [1,2]. In Libya, the Great Man-Made River (GMMR) project is the infrastructural backbone of this nexus, transporting 6.6 million m^3 of water daily from southern fossil aquifers to northern coastal cities [1,3]. However, the 4-meter diameter PCCP pipes, wrapped in 8 kilometers of high-tensile steel wire per segment, are highly susceptible to chloride-induced corrosion [3,4]. This leads to the sudden rupture of wires and subsequent catastrophic pipe bursts, five of which have already occurred. Traditionally, pipeline management has been approached through isolated engineering disciplines [5,6]. Chemical engineers optimize Cathodic Protection (CP) systems—utilizing potentials as negative as -4 V in aggressive soils—while electrical engineers independently deploy Acoustic Emission (AE) sensors and Wireless Sensor Networks (WSN) to detect structural failures [6,7]. This siloed approach creates interdisciplinary conflicts: increasing the CP voltage to reach "passive" electrochemical states (~ -315 mV) often introduces impulsive noise and EMI that degrades the signal-to-noise ratio of AE sensors and rapidly accelerates node failure due to energy depletion [6,7].

To address these conflicts, this paper introduces an "Integrated Cognitive Pipeline" model. By leveraging the Pearson-RSM-NSGA-II optimization framework, this study demonstrates how to mathematically bridge electrochemical process control with low-power electronic constraints, ensuring that sustainable research directly translates into resilient infrastructure.

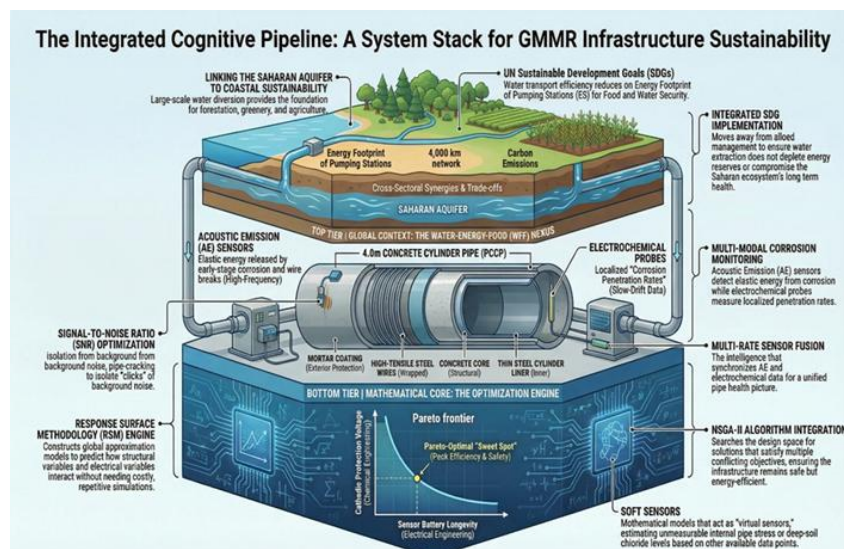


Figure 1. The Integrated Cognitive Pipeline conceptualized as a three-tier system stack, illustrating the flow from the global Water-Energy-Food Nexus down to the physical PCCP layer and the mathematical optimization engine

The proposed architecture transitions traditional pipeline monitoring into a three-tier Industrial Cyber-Physical System (iCPS). The system coordinates physical resources with cyber-analytical layers to ensure resiliency in the RF-harsh Saharan environment.

Tier 1 & 2: The Sensing and Edge Layer

The physical interface utilizes a dual-modality approach to capture the "4 Vs" of Big Data (Volume, Variety, Velocity, Veracity): The high-frequency transient waves from AE sensors address Velocity and Volume, while the steady-state electrochemical potentials provide Variety, which together are fused to ensure data Veracity. Acoustic Emission (AE) Sensors: Piezoelectric transducers (e.g., PAL R3I) mounted on the mortar coating detect transient elastic waves from wire fractures. In-network processing uses iterative average consensus algorithms to filter noise before transmission. Electrochemical Sensors: Geometrically optimized circular Interdigitated Electrodes (IDEs) monitor structural potentials and Polarization Resistance (R_p) [7,8]. Circular designs are prioritized to ensure a uniform electric field, reducing the "edge effects" that cause inaccurate corrosion readings in rectangular sensors.

Tier 3: The Industrial Big Data Decision Hub

Data is transmitted to a gateway for uncertainty-aware high-level data management (U-HDMA). This layer functions as a Digital Twin, employing a Maximum a Posteriori (MAP) fusion engine to combine high-frequency AE hits with low-frequency electrochemical data [5,9]. By accounting for an expanded uncertainty ($k=1.96$ for 95% confidence), the system distinguishes between sensor drift and genuine "extreme events," such as an imminent pipe burst.

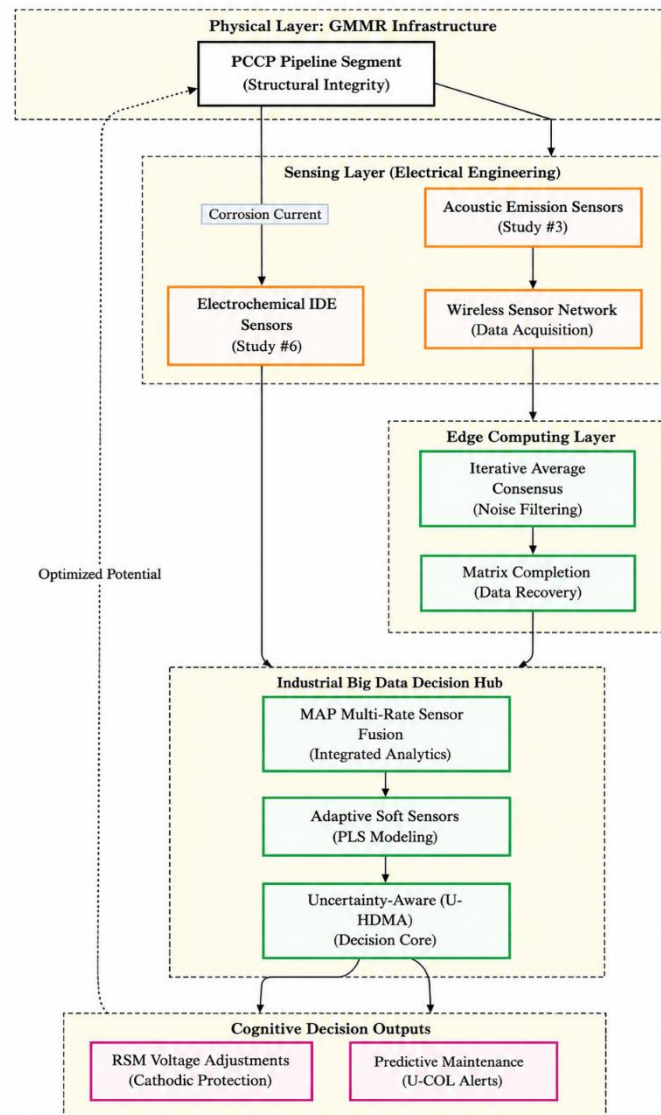


Figure 2. Data flow and logic architecture detailing the transition from physical acoustic and electrochemical sensing to uncertainty-aware cognitive decision outputs.

Methods

Multi-Objective Optimization via RSM

To resolve the interdisciplinary conflicts between aggressive chemical protection and electrical power constraints, the system employs a Pearson-RSM-NSGA-II framework.

Pearson Correlation Screening

Before modeling, a Pearson Correlation Coefficient analysis quantitatively assesses the linear relationship between design variables (e.g., IDE gap width) and performance metrics (e.g., SNR). This removes subjective bias and identifies "sensitive" parameters for the optimization range.

RSM Modeling and NSGA-II Optimization

The second-order polynomial response surface model (RSM) serves as a surrogate model to capture nonlinear mappings without the computational cost of full-scale simulations.

Input Factors (x): CP Excitation Voltage (0.5V–4.0V), IDE Finger Gap (mm), and Sensor Duty Cycle (%) [7,8,10].

Responses (Y): Polarization Resistance (R_p) ($k\Omega \cdot cm^2$), Sensor Battery Life (Months), and Signal-to-Noise Ratio (dB) [7,10].

The NSGA-II algorithm identifies the Pareto-optimal front. This allows engineers to pinpoint the exact voltage that maintains the rebar in a "passive" state (~ -315 mV) while ensuring the WSN nodes remain autonomous for an optimized lifespan of 22 months.

It should be noted that the response surface (Fig. 4) was generated by interpolating the 15 experimental runs, based on the RSM-NSGA-II framework [10] and electrochemical realities [7], into a regular grid to

visualize the multi-objective design space. Also, it should be mentioned that IDE gap and SNR were held constant for this specific simulation to isolate the voltage/duty cycle relationship.

Table 1. Multi-objective RSM-NSGA-II optimization results for corrosion mitigation and wireless sensor network longevity.

Run #	CP Excitation Voltage (V)	Sensor Duty Cycle (%)	Predicted Corrosion Rate (mm/year)	Sensor Battery Life (Months)
1	0.5	5	1.45	60
2	0.5	40	1.12	42.5
3	1	10	0.85	52
4	1	50	0.54	30.5
5	1.5	25	0.32	38
6	2	15	0.18	45
7	2	60	0.095	22
8	2.5	30	0.065	28.5
9	2.5	80	0.042	14
10	3	20	0.038	32
11	3	75	0.025	11.5
12	3.5	45	0.018	16
13	3.5	90	0.012	6.5
14	4	50	0.008	9
15	4	100	0.005	3.2

Data-Driven Innovations: Soft Sensors and Matrix Completion

Saharan infrastructure suffers from "blind spots" over 4,000 km of buried pipeline where excavation is unfeasible. The architecture overcomes this through two data-driven methods:

Adaptive Soft Sensors

Using Partial Least Squares (PLS) models, the hub implements Soft Sensors that predict difficult-to-measure variables (e.g., localized chloride ingress) using frequently sampled environmental inputs like soil temperature and moisture [5,9]. These models are updated periodically using mean and variance update algorithms to track time-varying process dynamics such as soil shifting or coating degradation.

Matrix Completion (MC) for Wide-Area Monitoring

By applying Matrix Completion (MC), the system can recover missing sensor data caused by node failures or wide sensor spacing. If physical sensors are spaced kilometers apart, the MC algorithm can "fill in" the health state of intermediate segments. This supplemental monitoring reduces requisite physical hardware by up to 40%, maintaining the "Just-in-Time" maintenance loop required for national water security [5,6].

Results

The Pearson-RSM-NSGA-II framework identifies a Pareto-optimal solution that maintains structural Polarization Resistance (R_p) above critical thresholds without exceeding the power limits of the WSN [7,10]. By preventing catastrophic blowouts (which release millions of cubic meters of water) and reducing the continuous power draw of over-voltage CP systems, the RSM-optimized network is projected to achieve up to a 10% reduction in total energy and water loss across the GMMR network.

The interdisciplinary conflict is mathematically visualized in (Figures 3 and 4).

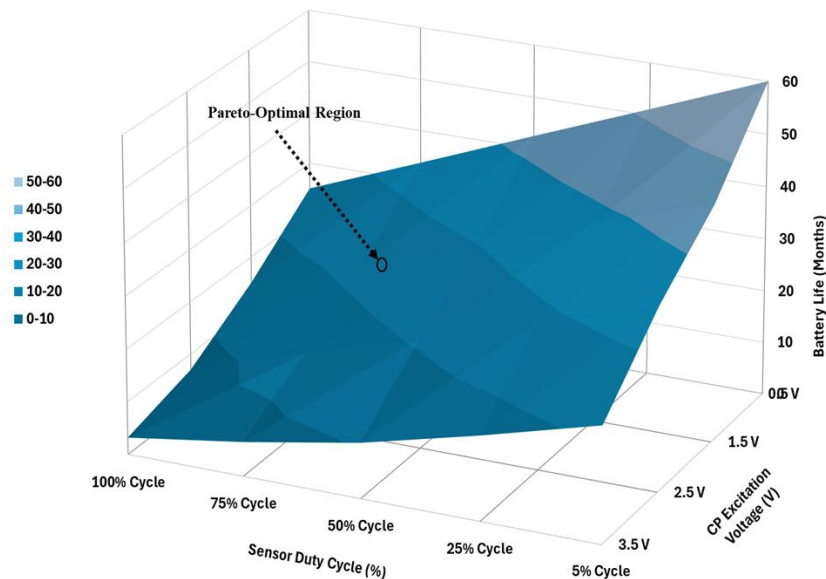


Figure 3. Response Surface of Wireless Sensor Node Battery Longevity vs. Operational Constraints.

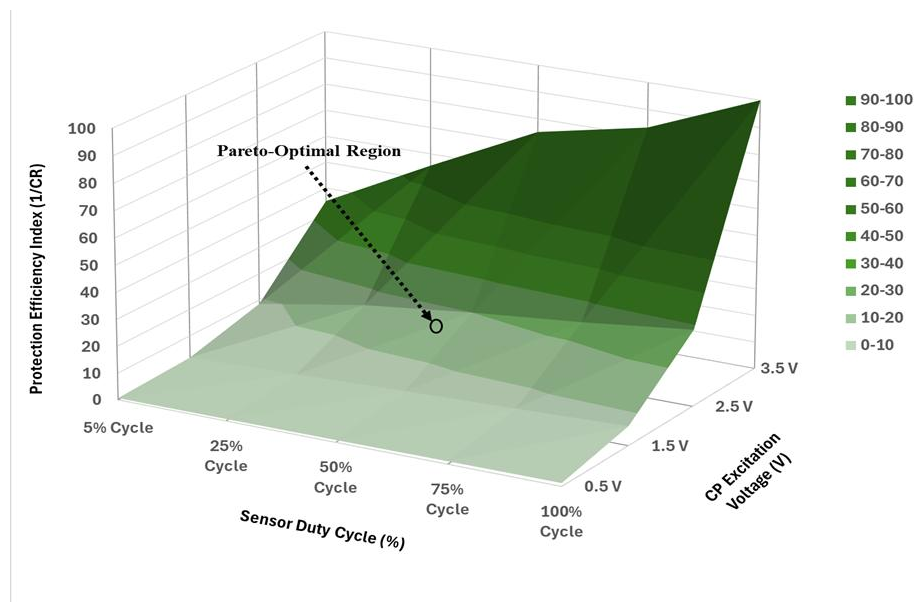


Figure 4. Response Surface of Electrochemical Protection Efficiency vs. Operational Control Factors.

The Response Surface for Battery Life (Figure 3) exhibits a sharp declivity as CP Excitation Voltage and Sensor Duty Cycle increase, representing the Electrical Engineering constraint. Conversely, the Protection Level surface (Figure 4) shows an exponential rise toward the 4.0V / 100% cycle region.

By overlaying these surfaces, the Pearson-RSM-NSGA-II framework identifies the Pareto-optimal 'ridge'—specifically around Run #7 (2.0V at 60% Duty Cycle). At this coordinate, the system maintains a passive electrochemical state (R_p stability) while preserving a sensor lifespan of nearly 2 years.

A comparative analysis of (Figures 3 and 4) reveals the fundamental interdisciplinary conflict of the GMMR monitoring system. While (Figure 4) shows that increasing the CP excitation voltage to -4.0V maximizes the protection level (reaching a peak efficiency, lowest corrosion rate (CR) \sim 0.005 mm/year), (Figure 3) demonstrates that this same setting reduces sensor battery life to a non-viable 3.2 months.

By selecting a 2.0V potential with a 60% duty cycle, the system achieves a 'High' protection state while maintaining an operational lifespan of 22 months—a 580% increase in longevity compared to the maximum-protection setting.

Discussion

Resolving Interdisciplinary Conflicts

As outlined in Section 1, the isolated optimization of CP currents creates detrimental EMI for wireless sensor networks. The Pearson-RSM-NSGA-II framework forces a mathematical compromise.

By treating IDE Finger Gap and CP Excitation Voltage as input factors, the system identifies a Pareto-optimal solution that maintains structural Polarization Resistance (R_p) above critical thresholds without exceeding the power limits of the WSN [7,10].

This allows the "Integrated Cognitive Pipeline" to dynamically adjust sampling rates based on the uncertainty-aware risk profile. During dry periods, when soil resistivity is high (up to 10,000 Ω -cm), and corrosion risk is low, sensors enter a resource-saving deep-sleep mode [7,6].

Conversely, following extreme rainfall events described in [2], the system detects a spike in soil conductivity and triggers the U-COL (Compliance with Operating Limits) protocol to temporarily transition the AE sensors to high-frequency sampling [2,6].

The surface in (Figure 4) illustrates the exponential increase in corrosion mitigation as Cathodic Protection (CP) voltage is intensified. While the peak at 4.0V represents maximum chemical passivity, the Integrated Cognitive Pipeline targets the plateau region at 2.0V to balance structural integrity with the energy constraints of the wireless sensing nodes.

Conclusion

The "Integration of Sciences" is a vital operational requirement for the sustainability of mega-infrastructure like the Great Man-Made River. This paper has demonstrated that Response Surface Methodology (RSM) serves as an effective mathematical bridge between Electrical and Chemical Engineering. By combining Acoustic Emission hardware, circular IDE sensors, and Industrial Big Data frameworks, the proposed Cognitive Pipeline achieves a synergistic reduction in operational waste [1,3,9]. Beyond technical resilience, this system addresses the WEF Nexus by safeguarding the Nubian Sandstone Aquifer. Through an estimated 10% gain in water conveyance efficiency and pumping energy savings, this integrated approach ensures that Libya's infrastructure can withstand the unpredictable climatic stressors of the 21st century [6,7].

References

1. Liu J, et al. Nexus approaches to global sustainable development. *Nat Sustain.* 2018 Sep;1(9):466-476.
2. Habib MA, et al. Sustainability benefits of AI-based engineering solutions for infrastructure resilience in arid regions against extreme rainfall events. *Discover Sustainability.* 2024;1(5):278.
3. Salih M. The Great Man-Made River Project: Case Studies in Project Management [dissertation]. UK: University of the West of Scotland; 2021.
4. Elfergani HA, et al. Acoustic emission analysis of prestressed concrete structures. *J Phys Conf Ser.* 2011;305(1):012076.
5. Udugama BC, et al. The role of big data in industrial (bio)chemical process operations. *Ind Eng Chem Res.* 2020 Aug 26;59(34):15283-15297.
6. Tzagkarakis G, et al. Signal and data processing techniques for industrial cyber-physical systems. In: *Cyber Physical Systems: From Theory to Practice.* CRC Press; 2015. p. 181-226.
7. Khan AA, et al. Frontiers and challenges in electrochemical corrosion monitoring: surface and downhole applications. *Sensors.* 2020 Nov;22(22):6583.
8. Elizabeth CA, et al. From rectangular to circular geometries: enhancing real-time corrosion sensing through geometrical optimization of IDE based electrochemical sensor. *Discover Sensors.* 2025;1(1):8.
9. Wang Z, Liu C. Monitoring chemical processes using judicious fusion of multi-rate sensor data. *Sensors.* 2019 Oct;10(10):2240.
10. Zhao Y, et al. Multi-objective optimization of EV battery packs: lightweight and safety via Pearson-RSM-NSGA-II. *J Eng Res.* 2025. [Epub ahead of print].