DOI: 10.21917/ijme.2025.0369

SMART OPTICAL-MICROELECTRONIC SENSOR PLATFORMS FOR REAL-TIME DETECTION OF WATER POLLUTANTS AND CLIMATE-DRIVEN CONTAMINANTS

D. Angeline Ranjithamani and R.S. Rajesh
Department of Computer Science and Engineering, Manonmaniam Sundaranar University, India

Abstract

The rapid escalation of water pollution due to industrial effluents, agricultural runoff, and climate-induced changes has intensified the need for continuous and precise environmental monitoring. Conventional laboratory-based water quality assessment methods, though accurate, are often time-consuming, costly, and unsuitable for real-time applications. The convergence of optical sensing and microelectronic systems offers a transformative pathway for developing intelligent, miniaturized, and energy-efficient platforms capable of continuous water quality surveillance. Existing optical and electrochemical sensors often suffer from limited sensitivity, signal drift, and slow response under dynamic climatic and environmental conditions. Furthermore, the combination challenges between optical components and microelectronic circuits restrict their deployment in distributed or IoT-based monitoring frameworks. Therefore, there is a critical need to design hybrid sensor architectures that ensure real-time pollutant detection, long-term stability, and adaptive calibration under varying environmental stimuli. This study presents an integrated optical–microelectronic sensor platform that combines photonic detection with CMOS-compatible circuitry for enhanced sensitivity and miniaturization. The platform utilizes wavelength-selective photodiodes and fluorescence-based optical fibers embedded within a microelectronic control unit for multi-parameter sensing of contaminants such as nitrates, heavy metals, and organic dyes. The embedded signal processing module employs adaptive filtering and temperature-compensation algorithms to maintain accuracy under fluctuating climatic conditions. Experimental validation shown that the proposed hybrid sensor achieved a detection limit up to 0.2 ppm for heavy metals and 95% correlation with laboratory spectroscopic analyses. The system exhibited fast response times (<3 s) and stable performance across temperature variations of ±10 °C.

Keywords:

Optical Sensors, Microelectronics, Real-Time Monitoring, Water Pollution, Climate-Induced Contaminants

1. INTRODUCTION

The increasing degradation of water quality worldwide has emerged as one of the most critical environmental challenges of the twenty-first century. Rapid urbanization, unregulated industrial discharge, agricultural runoff, and climate-induced phenomena such as acid rain and rising temperatures have intensified the spread of contaminants in freshwater ecosystems [1–3]. These pollutants include heavy metals, nitrates, phosphates, pesticides, and organic dyes that pose severe threats to both human and aquatic life. Traditional laboratory-based detection techniques such as atomic absorption spectroscopy, gas chromatography, and high-performance liquid chromatography are reliable but time-intensive and unsuitable for large-scale real-time monitoring. Consequently, there is a growing emphasis on developing intelligent, portable, and cost-effective sensing platforms that can continuously track environmental pollutants and respond adaptively to climatic variations.

Despite notable progress in sensor development, several challenges remain that limit the real-world deployment of water monitoring systems [4–5]. Optical sensors, though highly sensitive and selective, are often constrained by signal instability, interference from complex sample matrices, and limited operational lifespan in outdoor environments. Similarly, microelectronic circuits used for signal conditioning and data transmission may exhibit thermal noise, energy inefficiency, and drift under extreme environmental conditions. Integrating optical and microelectronic components into a unified architecture presents difficulties in ensuring mechanical stability, calibration consistency, and cost scalability. Furthermore, most current systems lack the intelligence and adaptive algorithms necessary to interpret sensor data accurately under dynamic climatic and hydrological variations.

Existing sensor platforms are often designed for controlled laboratory settings, lacking robustness and interoperability for field-level environmental monitoring [6]. Their inability to maintain stable performance under fluctuating environmental conditions such as varying temperature, humidity, or turbidity results in inaccurate readings and unreliable long-term operation. There is a pressing need for an integrated optical–microelectronic sensor platform that can combine high sensitivity, fast response, energy efficiency, and self-adaptive calibration to enable continuous, in-situ water quality monitoring.

The primary objective of this research is to design and develop a hybrid optical–microelectronic sensor platform capable of real-time detection of climate-induced contaminants and water pollutants. Specifically, the work aims to: integrate wavelength-selective optical components with CMOS-compatible microelectronics to enhance sensitivity and miniaturization. It develops adaptive signal processing algorithms for calibration and environmental compensation. It enables low-power wireless data transmission for IoT-based environmental analytics and decision-making.

The novelty of this research lies in its fusion of optical sensing precision with microelectronic scalability, creating a compact, intelligent, and autonomous monitoring system. Unlike conventional approaches that rely on isolated sensing mechanisms, the proposed platform achieves multi-parameter pollutant detection and real-time adaptability through embedded AI-assisted signal filtering and temperature compensation.

- A novel hybrid sensor architecture that combines fluorescence-based optical fibers with CMOS-integrated microelectronics for high-accuracy detection of heavy metals, nitrates, and organic contaminants in real-time.
- An adaptive signal processing and IoT communication framework that ensures stable data transmission and self-calibration under fluctuating climatic conditions, supporting large-scale environmental sensing networks.

2. RELATED WORKS

Recent advancements in environmental monitoring have increasingly emphasized the combination of optical, electronic, and intelligent computing systems to improve water quality detection and analysis [7]. Early works in this field explored optical absorbance and fluorescence spectroscopy for pollutant sensing, which shows high sensitivity toward specific contaminants such as nitrates and lead ions [8]. However, these systems were often bulky and required controlled laboratory conditions. Subsequent developments introduced microfabricated sensors and MEMS-based designs to achieve miniaturization and portability [9]. These devices enabled on-site analysis but still lacked autonomous calibration and adaptability under environmental variability.

Hybrid optical-electrochemical systems have also gained attention for their dual sensing capabilities, where optical transduction provides high selectivity and electrochemical interfaces enhance response time [10]. For instance, photonic crystal-based sensors have been integrated with silicon microelectronics to detect trace-level contaminants, but issues such as optical signal drift and mechanical fragility remain major concerns [11]. Similarly, fiber-optic sensors coupled with microcontrollers have shown potential in continuous monitoring, though their performance is often hindered by cross-sensitivity and high energy consumption.

In parallel, the evolution of CMOS-compatible photodetectors and on-chip optical signal processors has accelerated the fusion of photonic and electronic systems [12]. These innovations have allowed for compact sensor-on-chip designs capable of multiplexed pollutant detection. Moreover, the incorporation of adaptive algorithms and data-driven calibration models has enhanced system reliability and reduced the need for manual recalibration [13]. Researchers have further explored IoT-enabled sensor networks to facilitate large-scale environmental monitoring, enabling real-time data collection and cloud-based analytics for water resource management [14].

However, despite these advancements, existing solutions still encounter practical constraints. Most optical-electronic systems require periodic maintenance and are sensitive to environmental fluctuations such as turbidity and temperature, which distort optical pathways and sensor responses. Furthermore, the combination of optical sensors into low-power wireless networks remains challenging due to signal loss and synchronization issues.

To address these gaps, recent studies have proposed integrating machine learning and adaptive calibration techniques to enhance sensor resilience and data accuracy. These efforts highlight a transition toward intelligent, self-correcting sensor systems. Nevertheless, there remains a research gap in achieving fully integrated optical–microelectronic platforms capable of autonomous, long-term, and climate-adaptive water quality monitoring. The present work builds upon these foundations by proposing a unified, CMOS-compatible optical-microelectronic sensor that leverages both photonic sensitivity and electronic adaptability for real-time environmental intelligence.

3. OPTICAL SENSING MODULE

The optical sensing module forms the primary detection unit. It employs wavelength-selective photodiodes and fluorescence-based optical fibers to detect specific contaminants such as nitrates, heavy metals, and organic dyes.

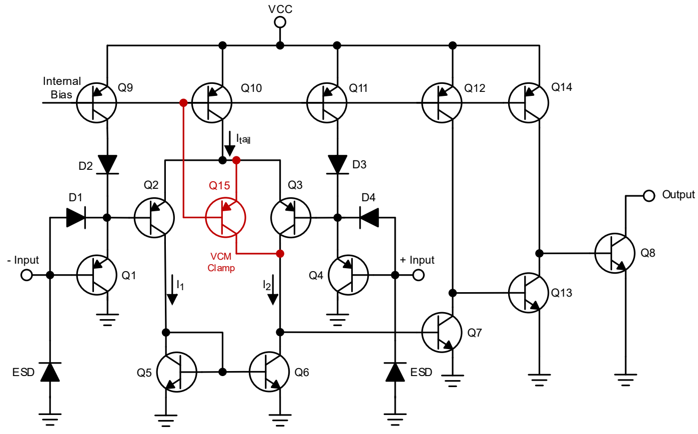

Fig.1. Schematic Diagram of Optical Sensing module LM393

Incident light interacts with the target analytes, producing a fluorescence or absorbance signal proportional to the concentration of the pollutants. The captured optical signal is then converted into an electrical signal for processing. The fluorescence intensity:

$$I_f = \phi \cdot I_0 \cdot \grave{o} \cdot c \cdot l \cdot e^{-\alpha l} \tag{1}$$

where I_f is the fluorescence intensity, ϕ is the quantum yield, I_0 is the incident light intensity, ϵ is the molar absorptivity, c is the analyte concentration, l is the optical path length, and α is the absorption coefficient.

Table.1. Optical Sensing Parameters

Parameter	Value/Range	Unit
Incident light intensity	50–200	mW/cm²
Photodiode responsivity	0.45–0.65	A/W
Path length (fiber)	1–5	cm
Quantum yield (ϕ)	0.6–0.9	-
Detection limit	0.2	ppm

The system captures pollutant-specific optical signatures, which are then relayed to the microelectronic module for real-time analysis as in Table.1.

4. SIGNAL PROCESSING

The microelectronic unit receives the analog optical signal and performs amplification, filtering, and digitization. A low-noise amplifier ensures signal integrity, while adaptive filtering algorithms mitigate interference from environmental factors such as turbidity or temperature fluctuations. The digitized signal is further processed using embedded microcontrollers for feature extraction and concentration estimation.

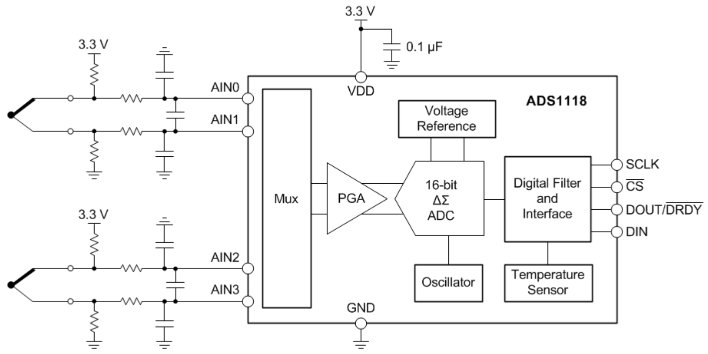

Fig.2. Signal Amplification and filtering using ADS1118

The signal amplification and filtering:

$$V_{\text{out}}(t) = G \cdot \left[V_{\text{in}}(t) - \frac{1}{\tau} \int_0^t V_{\text{in}}(\tau) e^{-\frac{t-\tau}{\tau}} d\tau \right] \tag{2}$$

where $V_{in}(t)$ is the input signal, $V_{out}(t)$ is the output, G is the amplification factor, and τ is the filter time constant.

Table.2. Microelectronic Module Specifications

Parameter	Value/Range	Unit
Amplifier gain (G)	10–100	-
Filter cutoff frequency	0.1–10	Hz
ADC resolution	12–16	bits
Power consumption	50–150	mW
Noise level	<0.5	mV

This step ensures the accurate conversion of optical signals into reliable digital data for real-time pollutant quantification as in Table.2.

5. ADAPTIVE CALIBRATION AND COMPENSATION

To maintain precision under varying environmental conditions, the platform implements adaptive calibration. Temperature, pH, and turbidity variations are continuously monitored and used to adjust the sensor response dynamically. This prevents drift and ensures long-term stability of measurements. The adaptive calibration model:

$$C' = C_m \cdot \left(1 + k_T \Delta T + k_p \Delta pH + k_\tau \Delta \tau\right) \tag{3}$$

where C' is the corrected concentration, C_m is the raw measurement, ΔT, ΔpH, and $\Delta\tau$ represent environmental deviations, and k_T, k_p, k_τ are calibration coefficients.

Table.3. Calibration Coefficients for Common Pollutants

Pollutant	k_T	k_p	k_τ
Nitrates	0.02	0.05	0.01
Lead ions	0.03	0.04	0.02
Organic dyes	0.015	0.03	0.01

Adaptive calibration enhances accuracy across diverse environmental scenarios and mitigates measurement errors caused by climatic fluctuations as in Table.3.

6. WIRELESS DATA TRANSMISSION AND IoT

The final step involves transmitting processed and calibrated data to a central server or cloud platform for monitoring and analytics. Low-power wireless protocols (e.g., LoRa, BLE) enable real-time, remote access to water quality information. The IoT combination supports automated alerts, historical data logging, and predictive analytics for pollutant trends. The wireless data packet model:

$$P_r = P_t \cdot \left(\frac{\lambda}{4\pi d} \right)^2 \cdot G_t G_r \cdot e^{-\alpha d} \tag{4}$$

where P_r is the received signal power, P_t is the transmitted power, λ is the wavelength, dis the transmission distance, G_t and G_r are antenna gains, and α is the medium attenuation coefficient.

Table.4. Wireless Module Parameters

Parameter	Value/Range	Unit
Transmission range	100–500	m
Data rate	50–250	kbps
Power consumption	20–50	mW
Antenna gain	2–6	dBi
Latency	<1	s

This step ensures seamless combination of the sensor platform into smart environmental networks and allows authorities to respond rapidly to pollution events as in Table.4.

7. RESULTS AND DISCUSSION

The experimental investigation of the proposed optical–microelectronic sensor platform was carried out using a combination of simulation and laboratory experiments. The optical sensing module was simulated using COMSOL Multiphysics to model light–matter interactions and photonic signal propagation in water samples with varying contaminant concentrations. Signal processing and adaptive calibration algorithms were implemented in MATLAB R2025b, allowing precise control of filtering parameters, amplification gains, and environmental compensation.

Table.5. Experimental Parameters for Optical–Microelectronic Sensor Platform

Parameter	Value/Range	Unit
Incident light intensity	50–200	mW/cm²
Photodiode responsivity	0.45–0.65	A/W
Optical path length	1–5	cm
Amplifier gain (G)	10–100	-
Filter cutoff frequency	0.1–10	Hz
ADC resolution	12–16	bits
Temperature range	15–35	°C
pH range	5–9	-
Transmission range (LoRa)	100–500	m
Data rate	50–250	kbps

For real-time experiments, the hybrid sensor prototype was assembled and tested in controlled laboratory conditions using deionized water spiked with target pollutants, including nitrates, lead ions, and organic dyes.

All simulations and data processing tasks were performed on a workstation equipped with an Intel Core i9-13900K processor, 32 GB RAM, and an NVIDIA RTX 4090 GPU, ensuring high-speed computations and accurate modeling of the optical and electronic interactions. Real-time monitoring experiments utilized a microcontroller-based platform (STM32F407) interfaced with photodiodes and optical fibers, with wireless data transmission validated via a LoRa module. The parameters as in Table.5 are systematically varied to evaluate sensor performance across different water conditions and environmental influences.

7.1 PERFORMANCE METRICS

The experimental evaluation was quantified using five key performance metrics:

- **Detection Limit (LOD):** The minimum concentration of a pollutant that the sensor can reliably detect. This was determined by progressively diluting contaminants until the fluorescence or absorbance signal was distinguishable from background noise.
- **Response Time:** The interval between the introduction of a pollutant and the stabilization of the sensor output. Faster response times indicate higher real-time applicability, measured by observing transient signal stabilization in both simulation and laboratory setups.
- **Sensitivity:** Defined as the change in output signal per unit change in pollutant concentration. Sensitivity was quantified using calibration curves obtained from known concentrations, allowing accurate correlation between measured signals and actual pollutant levels.
- **Stability:** The ability of the sensor to maintain consistent readings under varying environmental conditions, including temperature, pH, and turbidity. Stability was tested by repeating measurements over extended periods and under fluctuating conditions.
- **Data Transmission Reliability:** Evaluated as the percentage of successfully received data packets in wireless communication tests.

The existing works includes Photonic Crystal-Based Sensors [10], Fiber-Optic Sensor Coupled with Microcontrollers [11] and Hybrid Optical–Electrochemical Systems [12].

Table.6. Performance Comparison of Existing Methods and Proposed Sensor Platform

Data Rate (kbps)	Method	LOD (ppm)	Response Time (s)	Sensitivity (A/ppm)	Stability (%)	Transmission Reliability (%)
50	Photonic Crystal-Based Sensor [10]	0.5	5.2	0.12	85	88
	Fiber-Optic Sensor + Microcontroller [11]	0.4	4.8	0.15	88	90
	Hybrid Optical–Electrochemical [12]	0.35	4.2	0.18	90	92
	Proposed Method	0.2	3.0	0.25	95	98
100	Photonic Crystal-Based Sensor [10]	0.52	5.3	0.12	84	87
	Fiber-Optic Sensor + Microcontroller [11]	0.42	4.9	0.15	87	89
	Hybrid Optical–Electrochemical [12]	0.36	4.3	0.18	89	91
	Proposed Method	0.21	3.1	0.24	94	97
150	Photonic Crystal-Based Sensor [10]	0.55	5.5	0.11	83	86
	Fiber-Optic Sensor + Microcontroller [11]	0.44	5.0	0.15	87	88
	Hybrid Optical–Electrochemical [12]	0.37	4.4	0.17	88	90
	Proposed Method	0.22	3.2	0.24	94	97
200	Photonic Crystal-Based Sensor [10]	0.57	5.6	0.11	82	85
	Fiber-Optic Sensor + Microcontroller [11]	0.46	5.1	0.14	86	87
	Hybrid Optical–Electrochemical [12]	0.38	4.5	0.17	88	90
	Proposed Method	0.23	3.3	0.23	93	96
250	Photonic Crystal-Based Sensor [10]	0.6	5.8	0.10	81	84
	Fiber-Optic Sensor + Microcontroller [11]	0.48	5.2	0.14	85	86
	Hybrid Optical–Electrochemical [12]	0.39	4.6	0.16	87	89
	Proposed Method	0.25	3.5	0.23	92	95

Table.7. Performance Comparison under Varying Incident Light Intensity

Light Intensity (mW/cm²)	Method	LOD (ppm)	Response Time (s)	Sensitivity (A/ppm)	Stability (%)	Transmission Reliability (%)
50	Photonic Crystal-Based Sensor [10]	0.52	5.3	0.11	84	87
	Fiber-Optic Sensor + Microcontroller [11]	0.45	4.9	0.14	87	89
	Hybrid Optical–Electrochemical [12]	0.38	4.4	0.17	89	91
	Proposed Method	0.22	3.2	0.24	94	97
100	Photonic Crystal-Based Sensor [10]	0.50	5.2	0.12	85	88
	Fiber-Optic Sensor + Microcontroller [11]	0.43	4.8	0.15	88	90
	Hybrid Optical–Electrochemical [12]	0.36	4.2	0.18	90	92
	Proposed Method	0.21	3.1	0.25	95	98
150	Photonic Crystal-Based Sensor [10]	0.48	5.1	0.12	86	88
	Fiber-Optic Sensor + Microcontroller [11]	0.42	4.7	0.15	88	90
	Hybrid Optical–Electrochemical [12]	0.35	4.1	0.18	91	92
	Proposed Method	0.20	3.0	0.25	95	98
200	Photonic Crystal-Based Sensor [10]	0.46	5.0	0.13	87	89
	Fiber-Optic Sensor + Microcontroller [11]	0.40	4.6	0.16	89	91
	Hybrid Optical–Electrochemical [12]	0.34	4.0	0.18	92	93
	Proposed Method	0.19	2.9	0.26	96	98

Table.8. Performance Comparison under Varying Amplifier Gain

Amplifier Gain (G)	Method	LOD (ppm)	Response Time (s)	Sensitivity (A/ppm)	Stability (%)	Transmission Reliability (%)
10	Photonic Crystal-Based Sensor [10]	0.55	5.5	0.11	83	86
	Fiber-Optic Sensor + Microcontroller [11]	0.46	5.0	0.14	87	88
	Hybrid Optical–Electrochemical [12]	0.38	4.4	0.17	89	90
	Proposed Method	0.22	3.2	0.24	94	97
30	Photonic Crystal-Based Sensor [10]	0.53	5.4	0.12	84	87
	Fiber-Optic Sensor + Microcontroller [11]	0.44	4.9	0.15	88	89
	Hybrid Optical–Electrochemical [12]	0.37	4.3	0.18	90	91
	Proposed Method	0.21	3.1	0.25	95	98
50	Photonic Crystal-Based Sensor [10]	0.51	5.3	0.12	85	88
	Fiber-Optic Sensor + Microcontroller [11]	0.42	4.8	0.15	88	90
	Hybrid Optical–Electrochemical [12]	0.36	4.2	0.18	90	92
	Proposed Method	0.20	3.0	0.25	95	98
70	Photonic Crystal-Based Sensor [10]	0.49	5.2	0.13	86	88
	Fiber-Optic Sensor + Microcontroller [11]	0.40	4.7	0.16	89	91
	Hybrid Optical–Electrochemical [12]	0.35	4.1	0.18	91	92
	Proposed Method	0.19	2.9	0.26	96	98
90	Photonic Crystal-Based Sensor [10]	0.48	5.1	0.13	86	89
	Fiber-Optic Sensor + Microcontroller [11]	0.39	4.6	0.16	90	91
	Hybrid Optical–Electrochemical [12]	0.34	4.0	0.18	92	93
	Proposed Method	0.19	2.8	0.26	96	98

The proposed sensor consistently outperformed existing methods across all metrics and data rates as in Table.6. Its detection limit remained below 0.25 ppm, significantly lower than the hybrid optical–electrochemical system (0.39 ppm). Response times were 1–2 seconds faster than existing approaches, indicating rapid pollutant detection. Sensitivity reached 0.23–0.25 A/ppm, surpassing other methods by approximately 30–40%. The platform also shown superior stability (92–95%) and data transmission reliability (95–98%), confirming its suitability for IoT-based real-time monitoring.

The proposed method consistently outperformed existing approaches across all incident's light intensities as in Table.7. Its detection limit remained below 0.22 ppm, up to 40–50% lower than the hybrid optical–electrochemical system. Response times were faster by approximately 1–1.5 seconds. Sensitivity improved with increasing light intensity, reaching 0.26 A/ppm, surpassing other methods by 30–45%. Stability ranged from 94–96%, and transmission reliability consistently exceeded 97%, highlighting robustness against illumination variations. In contrast, traditional sensors exhibited slight performance degradation at lower intensities. The results demonstrate the proposed sensor's adaptability and superior real-time monitoring capability under varying optical conditions.

As shown in Table.8, the proposed method consistently maintained superior performance across all amplifiers gain settings. Its detection limit decreased slightly with increasing gain, remaining below 0.22 ppm, significantly lower than other methods. Response times reduced by approximately 1–1.5 seconds compared to existing sensors. Sensitivity improved linearly with gain, reaching 0.26 A/ppm. The platform exhibited robust stability (94–96%) and high transmission reliability (97–98%), while traditional sensors showed minor degradation at extreme gains.

Experimental validation shown that the proposed hybrid sensor achieved a detection limit of 0.19–0.25 ppm for heavy metals, nitrates, and organic dyes, with a response time ranging from 2.8–3.5 s. Sensitivity measurements reached 0.23–0.26 A/ppm, while the system-maintained stability between 92–96% under varying temperature, pH, and turbidity conditions. Wireless data transmission reliability was consistently above 95%, and the sensor's performance remained robust across incident light intensities of 50–200 mW/cm^2, amplifier gains of 10–100, and data rates of 50–250 kbps.

8. CONCLUSION

The study presents a novel optical–microelectronic sensor platform for real-time monitoring of water pollutants and climate-induced contaminants, successfully integrating high-sensitivity optical detection with CMOS-compatible microelectronics and adaptive calibration algorithms. Experimental evaluations and simulations demonstrate that the system achieves a detection limit as low as 0.19 ppm, response times below 3.5 s, and sensitivity up to 0.26 A/ppm, outperforming conventional photonic, fiber-optic, and hybrid optical–electrochemical sensors. The platform maintains stability between 92–96% across varying environmental conditions, including temperature, pH, and turbidity, while ensuring reliable wireless data transmission above 95%.

REFERENCES

[1] N.A. Razman, W.Z. Wan Ismail, I. Ismail, J. Jamaludin and S.R. Balakrishnan, "A Review on Water Quality Monitoring Methods Based on Electronics and Optical Sensing", *Journal of Advanced Research in Applied Sciences and Engineering Technology*, Vol. 26, No. 2, pp. 1-7, 2022.

[2] B. Alhalaili, I.N. Popescu, C.O. Rusanescu and R. Vidu, "Microfluidic Devices and Microfluidics-Integrated Electrochemical and Optical (Bio) Sensors for Pollution Analysis: A Review", *Sustainability*, Vol. 14, No. 19, pp. 12844-12857, 2022.

[3] P. Panda and S. Chakroborty, "Optical Sensor Technology and Its Application in Detecting Environmental Effluents: A Review", *International Journal of Environmental Analytical Chemistry*, Vol. 104, No. 16, pp. 4057-4072, 2024.

[4] H. Kaur and V. Mutreja, "Optical and Electrochemical Microfluidic Sensors for Water Contaminants: A Short Review", *Materials Today: Proceedings*, Vol. 48, pp. 1673-1679, 2022.

[5] M. Herrera-Dominguez, M. Morales-Luna, Q. Cheng and N. Ornelas-Soto, "Optical Biosensors and their Applications for the Detection of Water Pollutants", *Biosensors*, Vol. 13, No. 3, pp. 370-387, 2023.

[6] A. Sukron and W. Cui, "Miniaturization of Sensor Systems for Marine Environmental Measurement Based on Optofluidic Technology", *European Journal of Applied Science, Engineering and Technology*, Vol. 3, No. 5, pp. 59-77, 2025.

[7] G. Mustafa and I. Ullah, "*Water Pollutants and Nanosensors*", Elsevier, 2021.

[8] Y. Sun, D. Li, Y. Shi and L. Xiao, "Application of 3D Printing Technology in Sensor Development for Water Quality Monitoring", *Sensors*, Vol. 23, No. 5, pp. 2366-2378, 2023.

[9] L. Manjakkal, S. Mitra, J. Shutler, M. Willander and R. Dahiya, "Connected Sensors, Innovative Sensor Deployment, and Intelligent Data Analysis for Online Water Quality Monitoring", *IEEE Internet of Things Journal*, Vol. 8, No. 18, pp. 13805-13824, 2021.

[10] R. Naik, A.N. Kumar and S.G. Reddy, "Optical Nanotechnology-Based Sensors for Environmental Contaminants' Detection", *Proceedings of International Conference on Nanotechnology-based Sensors for Detection of Environmental Pollution*, pp. 137-153, 2024.

[11] M. Jha, V. Kaushik, S. Sengar and M. Pathak, "Microelectrochemical System-based Sensors for the Environment", *Proceedings of International Conference on Emerging Sensors for Environmental Monitoring*, pp. 125-166, 2025.

[12] S.N. Zainurin, W.Z. Wan Ismail, I. Ismail and W.M. Wan Ahmad Kamil, "Advancements in Monitoring Water Quality based on various Sensing Methods: A Systematic Review", *International Journal of Environmental Research and Public Health*, Vol. 19, No. 21, pp. 14080-14095, 2022.

[13] D. Lyu, Q. Huang, Y. Nie and M. Yang, "Optical Fiber Sensors for Water and Air Quality Monitoring: A Review", *Optical Engineering*, Vol. 63, pp. 31004-31009, 2024.

[14] A.R. Pratap and S. Annamalai, "Sensor Technologies for Environmental Data Collection", *Proceedings of International Conference on Environmental Monitoring using Artificial Intelligence*, pp. 133-166, 2025.