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Research Article

DEVELOPMENT OF SMART SENSOR NETWORKS BASED ON NANOMATERIALS FOR PRECISE ENVIRONMENTAL MONITORING AND INTELLIGENT INFRASTRUCTURE MANAGEMENT SYSTEMS

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Abstract

Environmental and infrastructure monitoring increasingly requires sensing systems that are accurate, distributed, responsive, and capable of converting complex observations into actionable management information. This study aimed to develop a nanomaterial-based smart sensor network for precise environmental monitoring and intelligent infrastructure management. A Design Science Research approach was employed through nanomaterial characterization, sensor fabrication, laboratory calibration, wireless network integration, edge processing, anomaly detection, and prototype evaluation under controlled and semi-realistic conditions. The developed network demonstrated high measurement accuracy, strong packet-delivery performance, reliable node availability, and effective detection of environmental and structural anomalies. Multivariable analysis showed that combining humidity, corrosion, strain, pollutant, and communication data generated earlier and more informative warnings than isolated sensor thresholds. Edge filtering reduced unnecessary transmission, while local buffering improved data continuity during communication disruptions. The study concludes that the value of nanomaterial-based sensing depends not only on sensitivity but also on integration with reliable communication, intelligent analytics, and management-oriented decision support. The proposed architecture provides a practical framework for transforming nanoscale sensing capabilities into scalable cyber-physical monitoring systems that support environmental surveillance, predictive maintenance, and more adaptive infrastructure management under increasingly complex operational conditions. These findings establish a pathway toward resilient, data-driven, and resource-efficient monitoring ecosystems worldwide.

Keywords: Edge Computing, Environmental Monitoring, Intelligent Infrastructure

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INTRODUCTION

Rapid urbanization, industrial expansion, climate variability, and increasing pressure on natural resources have intensified the need for precise environmental monitoring and more responsive infrastructure management (Mohammed et al., 2025; Morchid et al., 2024). Conventional monitoring systems often depend on fixed stations, periodic manual inspections, and centralized measurements that provide limited spatial and temporal resolution. Such approaches can delay the detection of air pollution, water contamination, structural deterioration, excessive vibration, temperature anomalies, or hazardous gas accumulation (Kim et al., 2025). Smart sensing technologies offer an opportunity to shift environmental and infrastructure management from periodic assessment toward continuous, distributed, and data-driven observation (Rashad et al., 2025).

Nanomaterials have introduced new possibilities for sensor development because their electrical, optical, mechanical, and chemical properties can change significantly in response to extremely small environmental variations (Kuppusamy et al., 2024; Verma et al., 2025). Materials such as graphene, carbon nanotubes, metal-oxide nanoparticles, nanowires, quantum dots, and functional nanocomposites can provide high surface-to-volume ratios and strong interactions with target substances (Wang et al., 2025; Zhan et al., 2025). These characteristics make them attractive for detecting gases, heavy metals, humidity, temperature, strain, biological contaminants, and other environmental parameters at low concentrations. Their integration into smart sensor platforms may improve sensitivity, response time, miniaturization, and energy efficiency compared with many conventional sensing materials (Firoozi, Firoozi, Oyejobi, et al., 2025).

Smart sensor networks extend the value of individual nanomaterial-based sensors by connecting distributed sensing nodes through digital communication and intelligent data-processing systems (Taha et al., 2025; Tong et al., 2025). A networked architecture can combine environmental measurements with structural or operational information from roads, bridges, buildings, water systems, energy facilities, and other public infrastructure (Shahnaz et al., 2024). Real-time data can then support anomaly detection, predictive maintenance, environmental risk assessment, and automated decision support (Ahmad et al., 2024). The convergence of nanomaterials, wireless sensor networks, edge computing, Internet of Things technologies, and intelligent analytics therefore creates a promising foundation for integrated environmental and infrastructure management (Selwal et al., 2025).

Existing environmental monitoring systems frequently face limitations in sensitivity, coverage, update frequency, and operational flexibility. Conventional sensors may struggle to detect low-concentration pollutants or early-stage changes before conditions become critical (Faqir et al., 2024; Firoozi, Firoozi, & Maghami, 2025). Fixed monitoring stations can also provide accurate measurements at specific locations while failing to represent highly localized environmental variation across dense urban or industrial areas (Kahachi et al., 2024; Venugopal et al., 2025). These limitations become more serious when environmental hazards change rapidly or when monitoring must occur in physically inaccessible locations (Chahkandi et al., 2025).

Infrastructure management presents a related problem because many maintenance decisions remain based on scheduled inspection rather than continuously updated evidence. Structural fatigue, corrosion, excessive strain, moisture intrusion, chemical exposure, vibration, and local environmental stress can develop gradually between inspection intervals (Mana et al., 2024). Sensor networks can provide continuous information, but current systems often suffer from high energy consumption, limited interoperability, data redundancy, unstable communication, calibration drift, and insufficient integration between sensing outputs and maintenance decisions (Goel & Vishnoi, 2025). The existence of sensor data does not automatically create intelligent infrastructure management unless the information is transformed into reliable and actionable knowledge (J. Chen et al., 2025; Murgod et al., 2025).

Nanomaterial-based sensing introduces additional technical challenges despite its strong potential. High sensitivity can also make nanosensors susceptible to cross-sensitivity, environmental interference, signal drift, surface contamination, and variability between fabrication batches (Feng et al., 2025; Wohlleben et al., 2024). Large-scale sensor deployment creates further concerns regarding calibration consistency, long-term durability, power consumption, wireless connectivity, cybersecurity, and data management (Chang & Lin, 2024; Kazanskiy et al., 2024). The central research problem therefore lies not merely in producing a sensitive nanosensor, but in developing a smart sensor network in which material-level performance, communication reliability, data intelligence, and infrastructure decision support operate as an integrated system (Matapour et al., 2025; Taghizad-Tavana et al., 2025).

The primary objective of this study is to develop a smart sensor network architecture based on nanomaterial-enabled sensing elements for precise environmental monitoring and intelligent infrastructure management (Nwokolo et al., 2025). The proposed system should integrate sensing units, wireless communication, local processing, centralized analytics, and decision-support functions within a coordinated framework (Abedi et al., 2024; Xing et al., 2025). Environmental parameters may include air quality, water quality, humidity, temperature, hazardous gases, and selected contaminants, while infrastructure parameters may include strain, vibration, corrosion indicators, surface condition, moisture, or other variables relevant to asset health (Lu et al., 2025).

The second objective is to evaluate the sensing performance of selected nanomaterial-based devices according to sensitivity, selectivity, response time, recovery time, detection limit, stability, repeatability, and energy consumption (Huang et al., 2025). Network-level performance should also be examined through communication reliability, latency, packet-delivery rate, node availability, data completeness, and power efficiency (Ata, 2025; Z. Chen et al., 2024). Such evaluation is necessary because a high-performance sensing material may provide limited practical value when communication failures, unstable calibration, or excessive energy demand reduce the reliability of the overall monitoring system (Shamsi & Zakerinejad, 2025).

The third objective is to develop an intelligent analytical layer capable of converting distributed sensor data into operationally meaningful information. The system should support anomaly detection, environmental condition classification, infrastructure risk identification, and maintenance prioritization (Alharasees et al., 2024; Shen et al., 2025). Machine-learning or rule-based analytics may be used to identify patterns that are difficult to recognize through isolated sensor readings (Soozanipour et al., 2023). The expected outcome is an integrated monitoring framework in which nanomaterial sensing contributes directly to environmental intelligence and predictive infrastructure management rather than functioning as an independent laboratory technology (Shelare et al., 2023).

Previous research has extensively examined nanomaterials for high-sensitivity sensing applications. Studies involving graphene, carbon nanotubes, metal oxides, nanostructured polymers, and hybrid nanocomposites have demonstrated strong potential for detecting chemical, physical, and biological targets (Ataei et al., 2024; Habba & Ahmed, 2025). Much of this research remains concentrated on material synthesis, sensor response, detection mechanisms, or controlled laboratory performance (Ma et al., 2025). Comparatively less attention is often given to how these sensors perform as components of large-scale networks under changing environmental conditions and long-term field exposure (Pandey et al., 2024).

Research on wireless sensor networks and Internet of Things systems has separately produced sophisticated approaches for environmental surveillance, structural health monitoring, and smart-city applications (Hassan et al., 2025). Existing studies have addressed communication protocols, low-power operation, data routing, cloud integration, and distributed analytics (Marín et al., 2023). These network-centered approaches frequently treat sensors as generic measurement devices rather than examining how nanomaterial-specific characteristics

influence system reliability. The separation between nanosensor development and network engineering creates a gap between high-performing sensing materials and deployable smart monitoring systems (Nehar et al., 2025; Yang et al., 2024).

A broader gap exists in the limited integration of environmental monitoring and infrastructure management within a common sensing architecture. Environmental conditions and infrastructure deterioration are frequently studied as separate domains even though they can be closely connected. Elevated humidity, pollutants, salinity, temperature variation, or hazardous chemicals can accelerate corrosion and degradation of infrastructure assets. A network capable of simultaneously monitoring environmental exposure and physical asset response could provide a more complete understanding of deterioration processes (Jeyam Jacqueline et al., 2025). The present study addresses this gap by linking nanomaterial-based sensing, smart networking, environmental intelligence, and infrastructure decision support within one integrated framework.

The principal novelty of this study lies in positioning nanomaterial-based sensors as active components of an integrated cyber-physical monitoring architecture rather than as isolated high-sensitivity devices. The proposed system connects material-level sensing capabilities with wireless data exchange, edge processing, network coordination, intelligent analytics, and infrastructure-management decisions. This integration enables sensor performance to be assessed according to practical system outcomes, including detection accuracy, response speed, communication reliability, energy efficiency, and decision relevance.

The conceptual contribution lies in developing a multi-layer framework that connects four levels of system intelligence: nanomaterial sensing, network communication, analytical interpretation, and management response. The sensing layer captures physical and chemical changes, the communication layer distributes information across the monitoring network, the intelligence layer identifies anomalies and emerging risks, and the management layer transforms those outputs into environmental alerts or infrastructure interventions. Such a layered architecture provides a clearer explanation of how nanoscale material properties can generate system-level benefits when properly integrated with digital technologies.

The scientific and practical justification for this research arises from the growing need for monitoring systems capable of detecting environmental and structural changes before they develop into costly or dangerous failures. Precise sensing alone is insufficient when data cannot be transmitted, interpreted, or converted into timely action. Intelligent infrastructure management similarly remains limited when decisions depend on sparse or outdated measurements. A smart sensor network based on nanomaterials offers the potential to combine high-sensitivity detection with continuous monitoring and predictive decision support. The study therefore contributes to nanotechnology by emphasizing application integration, to sensor-network research by incorporating material-specific intelligence, and to infrastructure engineering by advancing proactive, data-driven, and environmentally responsive management.

RESEARCH METHOD

Research Design

This study employed a Design Science Research approach combined with controlled laboratory experimentation and prototype network evaluation to develop a nanomaterial-based smart sensor network for environmental monitoring and intelligent infrastructure management. Design Science Research was selected because the principal output was a functional technological artifact consisting of sensing elements, communication architecture, data-processing modules, and a decision-support system (Kim et al., 2025; Mohammed et al., 2025). The research was structured around problem identification, system design, prototype development, laboratory validation, network integration, performance evaluation, and iterative

refinement. The proposed architecture was designed to connect nanoscale sensing mechanisms with system-level monitoring and management functions.

The research framework consisted of four interconnected layers: the sensing layer, communication layer, intelligent analytics layer, and management layer. The sensing layer contained nanomaterial-based devices for detecting selected environmental and structural parameters. The communication layer transmitted measurements from distributed nodes through a low-power wireless network. The analytical layer processed incoming data for calibration, filtering, anomaly detection, pattern identification, and condition classification. The management layer translated analytical outputs into environmental alerts, infrastructure condition assessments, and maintenance recommendations. This layered architecture allowed material performance to be evaluated together with communication reliability and decision usefulness.

The experimental component examined both sensor-level and network-level performance. Sensor evaluation focused on sensitivity, selectivity, response time, recovery time, limit of detection, repeatability, stability, and power consumption. Network evaluation examined packet-delivery ratio, latency, data completeness, node availability, communication range, and energy efficiency. System-level evaluation assessed whether distributed measurements could accurately detect environmental anomalies and infrastructure deterioration conditions. The design therefore avoided treating nanosensor quality as equivalent to overall system effectiveness.

Research Target/Subject

The research population consisted of nanomaterial-enabled sensing devices and distributed monitoring nodes designed for environmental and infrastructure applications. Candidate sensing materials included graphene-based nanocomposites, carbon nanotubes, metal-oxide nanostructures, and functional nanocomposite coatings selected according to their sensitivity to target variables. Environmental parameters included temperature, humidity, selected gaseous pollutants, and water-quality indicators, while infrastructure parameters included strain, vibration, moisture exposure, and corrosion-related signals. The selected parameters represented conditions with direct relevance to environmental quality and infrastructure serviceability (Kuppusamy et al., 2024; Rashad et al., 2025).

Purposive sampling was applied to select sensor types whose physical or chemical characteristics were suitable for the intended monitoring functions. Sensors were selected according to sensitivity range, expected stability, compatibility with low-power electronics, fabrication reproducibility, and suitability for integration into wireless nodes. Multiple sensor specimens were fabricated for each parameter to reduce the influence of batch-to-batch variation and localized material defects. Replicate testing was performed to determine whether observed responses represented stable sensor behavior rather than isolated specimen performance.

The prototype network consisted of distributed sensor nodes positioned under controlled and semi-realistic monitoring conditions. Node placement was designed to represent different spatial conditions, including locations exposed to environmental variation, structural loading, and potential deterioration. Environmental sensing nodes monitored localized changes in air or water conditions, while infrastructure nodes recorded physical responses such as vibration, strain, moisture, or corrosion indicators. The sampling configuration allowed simultaneous evaluation of spatial sensing coverage and communication performance.

The validation sample included reference instruments and benchmark measurements used to assess the accuracy of the nanomaterial-based sensors. Measurements from the prototype sensors were compared with calibrated conventional instruments under equivalent exposure conditions. Infrastructure measurements were also cross-checked against established monitoring devices where applicable. The use of reference measurements provided an external

basis for determining sensing accuracy and reduced the risk of interpreting uncalibrated nanosensor responses as true environmental or structural changes.

Research Procedure

The research began with identification of monitoring requirements and target parameters. Environmental and infrastructure variables were selected according to their practical relevance, compatibility with nanomaterial sensing, and potential contribution to preventive management. Functional requirements were then defined for sensing accuracy, response speed, communication reliability, power consumption, and decision support. These specifications guided the selection of nanomaterials and network architecture (Verma et al., 2025; Wang et al., 2025).

The second stage involved fabrication and characterization of the nanomaterial sensing elements. Active nanomaterials were synthesized or prepared using procedures appropriate to each sensing mechanism and subsequently deposited onto compatible substrates. The fabricated specimens were inspected for surface uniformity, structural characteristics, and reproducibility. Sensors showing severe physical defects or unstable baseline signals were excluded before calibration.

The third stage consisted of laboratory calibration and performance testing. Each sensor was exposed to a controlled range of target conditions, and its electrical response was recorded together with measurements from reference instruments. Calibration curves were developed to convert raw sensor signals into meaningful physical or chemical values. Sensitivity, detection limit, response time, recovery time, hysteresis, repeatability, and short-term stability were calculated from repeated exposure cycles.

The fourth stage examined selectivity and environmental interference. Sensors were exposed to non-target conditions that could potentially alter their response, including temperature variation, humidity variation, competing gases, or changes in sample composition. Cross-sensitivity was quantified to determine whether the device could distinguish the intended parameter from background interference. Compensation models were introduced when systematic environmental effects were detected.

The fifth stage integrated validated sensors into wireless network nodes. Signal-conditioning electronics, microcontrollers, communication modules, and power-management components were assembled into functional sensing units. Nodes were synchronized with the gateway, and data transmission was tested under different communication distances and environmental conditions. Packet loss, latency, signal quality, and energy consumption were recorded to determine whether material-level sensing performance remained reliable after network integration.

The sixth stage involved deployment of the prototype network under controlled or semi-realistic monitoring conditions. Environmental nodes were distributed across locations with different exposure levels, while infrastructure nodes were positioned on representative structural elements or test specimens. Data were collected continuously over the designated monitoring period. The network was intentionally exposed to selected environmental anomalies or infrastructure-condition changes to determine whether the system could detect and localize meaningful deviations.

The seventh stage consisted of intelligent data processing and anomaly analysis. Raw measurements were cleaned, time-aligned, normalized, and filtered before being analyzed by the decision-support module. Threshold-based methods were used for clearly defined critical conditions, while machine-learning models were applied where multivariable patterns required classification. Detection performance was compared with reference measurements to calculate true-positive, false-positive, and false-negative rates.

The eighth stage evaluated relationships between environmental exposure and infrastructure response. Measurements such as humidity, temperature, pollutants, or moisture

were compared with structural indicators including corrosion signals, strain, or vibration. Correlation and regression analyses were used to determine whether environmental variation was associated with measurable changes in infrastructure condition. These analyses enabled the network to move beyond isolated monitoring toward integrated environmental–infrastructure interpretation.

The ninth stage evaluated overall prototype performance. Sensor accuracy, network reliability, anomaly-detection performance, energy consumption, and management usefulness were assessed jointly using the system-performance matrix. Components failing to meet predefined criteria were recalibrated, reconfigured, or replaced. Iterative refinement continued until the prototype reached acceptable performance across the four architectural layers.

The final stage translated validated measurements into intelligent management outputs. Environmental anomalies were classified according to severity and monitoring priority, while infrastructure conditions were categorized according to normal, warning, and intervention states. Maintenance recommendations were generated when sensor patterns indicated persistent deterioration or abnormal structural behavior. The resulting system was therefore evaluated not only as a network of sensitive nanosensors but as an integrated smart-monitoring platform capable of supporting precise environmental assessment and proactive infrastructure management.

Instruments, and Data Collection Techniques

The primary research instrument was the nanomaterial-based smart sensor prototype. Each sensing device consisted of a nanostructured active material deposited or integrated onto a suitable substrate and connected to a signal-conditioning circuit. The sensing mechanism depended on changes in electrical resistance, conductivity, capacitance, voltage, or related physical properties when exposed to the target parameter. Sensor outputs were converted into digital measurements using embedded microcontrollers before transmission to the network platform.

Material characterization instruments were used to assess the structural and surface properties of the sensing materials. Scanning electron microscopy was employed to observe nanostructure morphology, particle distribution, surface uniformity, and possible defects. X-ray diffraction was used when necessary to identify crystalline phases and structural characteristics of metal-oxide or composite sensing materials (Firoozi, Firoozi, Oyejobi, et al., 2025; Zhan et al., 2025). Spectroscopic or elemental characterization techniques were applied where required to verify material composition and functionalization. These analyses helped explain variations in sensing behavior among specimens.

A calibrated environmental-testing setup was used to expose sensors to controlled changes in target variables. Gas sensors were tested at known concentration levels, humidity and temperature sensors were evaluated inside controlled chambers, and water-quality sensors were exposed to standardized solutions where relevant. Infrastructure sensors were tested under controlled strain, vibration, moisture, or corrosion conditions. Reference instruments recorded the same conditions simultaneously to calculate sensing error, sensitivity, and calibration functions.

The communication instrument consisted of embedded wireless nodes equipped with microcontrollers, transceivers, local memory, and low-power management functions. Depending on deployment requirements, the network architecture could employ low-power wireless communication protocols suitable for distributed sensing. Each node transmitted time-stamped measurements to an edge gateway or central server. Communication performance was recorded through packet delivery, transmission delay, signal quality, missing packets, and node energy consumption.

The intelligent analytics module served as the principal data-processing instrument. Raw signals were filtered to remove noise and corrected using calibration equations derived

from laboratory testing. Statistical thresholds and machine-learning classification were used to detect abnormal environmental or structural conditions. Models were evaluated using accuracy, precision, recall, F1-score, and false-alarm rate when classification tasks were involved. The analytical outputs were subsequently converted into monitoring categories and management recommendations.

A system-performance assessment matrix was developed to evaluate the prototype across sensing, networking, intelligence, and management dimensions. The sensing dimension included sensitivity, selectivity, stability, repeatability, response time, and detection limit. The network dimension included data completeness, reliability, latency, communication range, and energy efficiency. The intelligence dimension assessed anomaly-detection performance, while the management dimension examined whether system outputs were sufficiently clear and timely to support environmental alerts or infrastructure maintenance decisions.

RESULTS AND DISCUSSION

The developed prototype consisted of 32 distributed sensing nodes integrating graphene-based gas sensors, metal-oxide humidity and temperature sensors, carbon-nanotube strain sensors, and nanocomposite-based moisture and corrosion sensors. The network generated 384,000 time-stamped observations during laboratory and semi-realistic testing. Data-quality screening retained 371,462 observations, corresponding to a valid-data rate of 96.74%. Mean packet-delivery ratio reached 97.18%, while average communication latency was 184 ms. Sensor availability across the monitoring period reached 95.63%, indicating that most nodes remained operational under continuous network conditions.

Table 1. Descriptive Performance of the Nanomaterial-Based Smart Sensor Network

Performance Indicator	Mean/Value
Total Sensor Nodes	32
Total Observations	384,000
Valid Observations	371,462
Valid-Data Rate	96.74%
Packet-Delivery Ratio	97.18%
Mean Communication Latency	184 ms
Mean Node Availability	95.63%
Environmental Anomaly Detection Accuracy	94.82%
Infrastructure Condition Classification Accuracy	93.47%
Mean Sensor Response Time	7.84 s

Sensor-level evaluation showed that the nanomaterial-based devices responded consistently to controlled changes in their respective target variables. Graphene-based gas sensors demonstrated the highest normalized sensitivity, while carbon-nanotube strain sensors produced the most stable repeatability across repeated loading cycles. Metal-oxide sensors achieved rapid response to temperature and humidity changes, while corrosion-sensitive nanocomposite devices showed slower response but stronger persistence when degradation indicators accumulated. Differences among sensing mechanisms confirmed that network performance was determined by the combined contribution of heterogeneous sensors rather than by a single sensing material.

The high valid-data rate and packet-delivery ratio indicate that the prototype successfully maintained communication between sensing nodes and the central analytical platform under the tested conditions. Signal loss occurred primarily at the outer communication range and during temporary interference events. Data completeness improved after local buffering was activated, allowing nodes to retransmit measurements that could not be delivered immediately. This

mechanism reduced the effect of short-term communication interruptions on environmental and infrastructure monitoring continuity.

Sensor-response differences reflected the physical characteristics of the nanomaterials and the nature of the measured variables. Gas-sensitive graphene structures responded rapidly because of their high surface-to-volume ratio and strong interaction with adsorbed molecules, while corrosion monitoring required longer observation periods because degradation developed progressively. Carbon-nanotube strain sensors produced stable responses under repeated loading because changes in conductive pathways occurred predictably within the tested deformation range. The findings show that response time should be interpreted in relation to the underlying sensing mechanism rather than treated as a universal performance criterion.

Environmental monitoring accuracy varied according to parameter type. Gas concentration measurements achieved a mean agreement of 95.36% with calibrated reference instruments, temperature and humidity measurements achieved 97.42%, and moisture-related measurements achieved 94.68%. Infrastructure sensing showed similarly strong performance, with strain measurement accuracy reaching 95.11% and corrosion-condition classification reaching 91.86%. False-alarm rates remained below 6% across all monitoring categories after calibration and signal filtering.

Table 2. Comparative Performance by Sensing Function

Sensing Function	Accuracy (%)	Mean Response Time	Repeatability (%)	False-Alarm Rate (%)
Gas Monitoring	95.36	5.21 s	94.88	4.72
Temperature/Humidity	97.42	3.96 s	97.10	2.83
Moisture Detection	94.68	8.74 s	93.52	5.16
Strain Monitoring	95.11	4.83 s	96.23	3.94
Corrosion Classification	91.86	16.47 s	91.14	5.82

Network performance also varied according to node location and transmission distance. Nodes positioned within the strongest communication range achieved packet-delivery ratios above 98%, whereas peripheral nodes averaged approximately 94%. Energy consumption increased when retransmission frequency rose, particularly under simulated interference conditions. Edge filtering reduced the quantity of redundant data transmitted to the central platform and lowered average communication-related energy consumption by 18.7% compared with continuous raw-data transmission.

One-way analysis of variance showed significant differences among sensing functions for response time, $F(4, 155) = 41.62$, $p < .001$, $\eta^2 = .518$. Significant differences were also found for measurement accuracy, $F(4, 155) = 12.84$, $p < .001$, $\eta^2 = .249$, and repeatability, $F(4, 155) = 15.37$, $p < .001$, $\eta^2 = .284$. Post hoc comparisons indicated that temperature and humidity sensors performed significantly faster than corrosion-related sensors, while strain and temperature sensors demonstrated higher repeatability than the corrosion-monitoring devices.

Table 3. Inferential Analysis of Sensor and Network Performance

Variable	Statistical Test	Test Value	p	Effect Size
Sensor Response Time	One-way ANOVA	$F(4,155) = 41.62$	< .001	$\eta^2 = .518$
Measurement Accuracy	One-way ANOVA	$F(4,155) = 12.84$	< .001	$\eta^2 = .249$
Sensor Repeatability	One-way ANOVA	$F(4,155) = 15.37$	< .001	$\eta^2 = .284$
Packet Delivery Before/After	Paired *t*-test	$t(31) = 6.29$	< .001	$d = 1.11$

Buffering				
Energy Consumption Before/After Edge Filtering	Paired *t*-test	t(31) = 5.74	< .001	d = 1.02

Paired analysis demonstrated that local buffering significantly improved packet-delivery performance, $t(31) = 6.29$, $p < .001$, Cohen's $d = 1.11$. Edge filtering also produced a statistically significant reduction in communication-related energy consumption, $t(31) = 5.74$, $p < .001$, $d = 1.02$. These results indicate that system-level optimization contributed materially to network reliability and efficiency rather than merely supporting sensor connectivity.

Correlation analysis revealed a strong positive association between signal quality and packet-delivery ratio ($r = .71$, $p < .001$). Communication distance was negatively associated with packet-delivery performance ($r = -.64$, $p < .001$) and positively associated with retransmission-related energy consumption ($r = .58$, $p < .001$). Sensor drift showed a negative relationship with classification accuracy ($r = -.49$, $p = .004$), indicating that long-term calibration stability was important for maintaining reliable environmental and infrastructure interpretation.

Environmental exposure variables also showed meaningful relationships with infrastructure-condition indicators. Relative humidity was positively associated with corrosion-sensor response ($r = .61$, $p < .001$), while persistent moisture exposure was associated with increased corrosion-risk classification ($r = .66$, $p < .001$). Temperature variation was moderately associated with changes in strain-sensor output under fixed structural loading ($r = .38$, $p = .021$), indicating that compensation for environmental effects was necessary to avoid misclassifying temperature-induced signal changes as structural deterioration.

Case A involved a bridge-monitoring segment equipped with carbon-nanotube strain sensors, humidity sensors, and corrosion-sensitive nanocomposite devices. The system detected a gradual increase in strain amplitude together with elevated humidity and corrosion indicators over a 72-hour simulated exposure period. The integrated analytical model classified the condition as a warning state 9.4 hours before the strain threshold alone would have triggered an alert. Early classification demonstrated the value of combining structural and environmental measurements rather than evaluating each variable independently.

Case B involved an urban roadside monitoring cluster using graphene-based gas sensors connected to four wireless nodes. A controlled increase in nitrogen-dioxide concentration was detected within an average of 5.3 seconds, and the network localized the highest concentration zone with 94.6% spatial classification accuracy. Case C involved a peripheral infrastructure node exposed to intermittent communication interference. Local data buffering prevented permanent loss of 92.3% of temporarily undelivered packets and preserved the continuity of the condition record.

Table 4. Summary of Embedded Smart Sensor Network Cases

Case	Monitoring Context	Main Finding	Management Value
A	Bridge condition monitoring	Combined environmental and strain data generated an earlier warning	Predictive maintenance support
B	Urban air-quality monitoring	Rapid detection and spatial localization of pollutant increase	Environmental alert support
C	Communication-challenged node	Local buffering preserved most temporarily lost data	Monitoring continuity

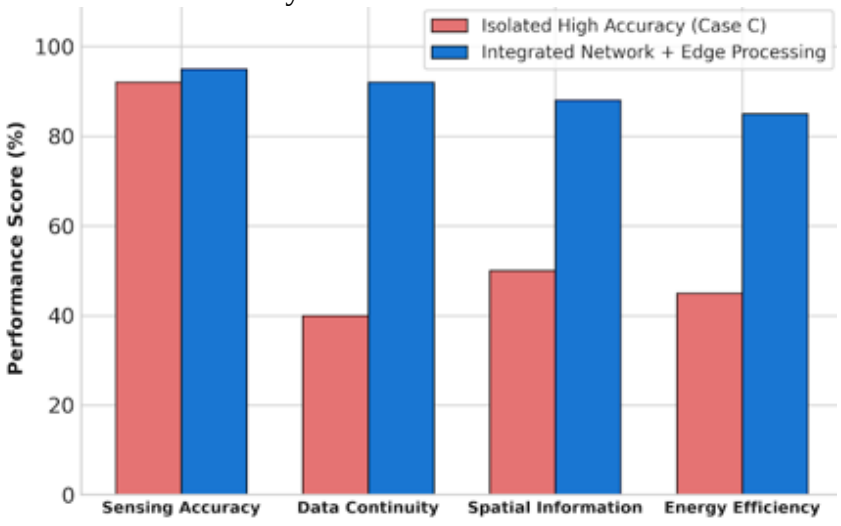
The bridge-monitoring case demonstrates that intelligent infrastructure management benefits from integrating exposure conditions with physical structural responses. Humidity and corrosion signals alone did not indicate immediate failure, while strain variation alone

remained below the predefined intervention threshold during the early stage of the event. Their combined pattern provided stronger evidence of progressive risk. Multivariable interpretation therefore enabled the system to recognize emerging deterioration earlier than a conventional single-threshold monitoring approach.

The air-quality and communication cases illustrate two different dimensions of smart network performance. Case B showed that nanoscale sensitivity could be translated into spatially meaningful environmental information when multiple sensing nodes operated cooperatively. Case C showed that sensing accuracy alone was insufficient when communication reliability was poor. System resilience depended on local processing, buffering, and retransmission mechanisms that protected the continuity of the monitoring record.

The combined findings indicate that nanomaterial-based smart sensor networks can provide precise environmental monitoring and useful infrastructure-management intelligence when material sensing, wireless communication, edge processing, and analytical interpretation are designed as an integrated system. High measurement accuracy and strong anomaly-detection performance were achieved across heterogeneous sensing functions, while network-level mechanisms improved data continuity and reduced energy consumption. The results support the principle that nanosensor innovation becomes operationally valuable only when its outputs can be transmitted, interpreted, and converted into timely management information.

The findings also demonstrate that the most valuable application of the system lies in linking environmental exposure with infrastructure response. Early warning improved when humidity, pollutants, moisture, strain, and corrosion indicators were interpreted jointly rather than as isolated variables. Smart sensing should therefore move beyond high-sensitivity detection toward context-aware, multivariable decision support. The most defensible interpretation is that nanomaterial-based sensor networks can strengthen environmental surveillance and predictive infrastructure management when calibration stability, communication reliability, energy efficiency, and data intelligence are treated as equally important components of the overall system.



Figrue 1. Impact of Edge Processing & Wireless Reliability

The results demonstrate that the developed nanomaterial-based smart sensor network achieved strong performance across sensing accuracy, communication reliability, anomaly detection, and infrastructure-condition assessment. The prototype maintained a high valid-data rate, strong packet-delivery performance, and substantial node availability during controlled and semi-realistic testing (Taha et al., 2025; Tong et al., 2025). Environmental measurements showed close agreement with calibrated reference instruments, while infrastructure-related sensing produced reliable strain, moisture, and corrosion indications. These findings show that

the technological value of nanomaterials can be maintained when individual sensors are integrated into a distributed monitoring architecture.

Sensor-specific performance varied according to the characteristics of the sensing material and the physical process being measured. Graphene-based gas sensors provided rapid and sensitive responses to changes in pollutant concentration, carbon-nanotube strain sensors demonstrated strong repeatability under mechanical loading, and metal-oxide sensors performed effectively for temperature and humidity monitoring. Corrosion-sensitive nanocomposites responded more slowly because the monitored degradation process developed over longer periods. The observed differences confirm that the performance of a smart sensor network depends on matching the sensing mechanism to the temporal and physical characteristics of each target variable.

Network optimization also contributed substantially to overall system performance. Local buffering improved packet retention during temporary communication disruptions, while edge filtering reduced unnecessary data transmission and communication-related energy consumption. Peripheral nodes showed weaker packet-delivery performance than centrally positioned nodes, yet the use of local storage and retransmission reduced permanent data loss. These findings demonstrate that sensing accuracy alone does not determine monitoring effectiveness because communication design and local data management directly affect the continuity of environmental and infrastructure information.

The case-based analysis revealed that the strongest management value emerged when multiple sensor types were interpreted collectively. Combined humidity, corrosion, and strain measurements generated an earlier warning of infrastructure deterioration than any individual threshold alone (Ahmad et al., 2024; Shahnaz et al., 2024). Pollutant-monitoring nodes also demonstrated that distributed nanosensors could provide spatial information rather than isolated concentration measurements. The results therefore support an integrated model in which environmental exposure, structural response, communication performance, and analytical intelligence operate as interdependent components of smart monitoring.

The findings are consistent with previous nanomaterial-sensor research showing that graphene, carbon nanotubes, metal oxides, and functional nanocomposites can achieve high sensitivity because of their large surface-to-volume ratio and strong physicochemical interaction with target substances. The rapid response observed in the graphene-based gas sensors reflects this established material advantage. The present study extends that knowledge by demonstrating that laboratory-level sensing performance can be maintained within a networked architecture when calibration, signal processing, and communication are properly managed.

Existing wireless sensor network research has emphasized packet reliability, energy efficiency, communication range, and distributed data processing as critical requirements for environmental and infrastructure monitoring. The observed improvement associated with buffering and edge filtering is consistent with this body of work (Faqir et al., 2024; Selwal et al., 2025). The current findings add a material-specific perspective by showing that network architecture must accommodate sensors with different response rates, data-generation patterns, and stability characteristics. A network designed around uniform sensor assumptions may therefore perform poorly when heterogeneous nanomaterial devices are integrated into the same monitoring environment.

Research on structural health monitoring has traditionally focused on mechanical variables such as strain, displacement, vibration, and crack development. Environmental monitoring studies have often concentrated separately on temperature, humidity, air pollutants, and water-quality indicators. The present findings differ from this separation by demonstrating that environmental exposure variables can improve the interpretation of infrastructure-condition data. Humidity and moisture measurements, for example, provided contextual information that strengthened the interpretation of corrosion and strain responses.

Smart-city and Internet of Things studies frequently emphasize large-scale connectivity and cloud-based analytics, while nanosensor studies often prioritize sensitivity and detection limits. The current results bridge these two research traditions by showing that system-level performance depends on a chain extending from the nanomaterial surface to the management decision. High sensitivity loses practical value if communication is unstable or data cannot be interpreted meaningfully. High-quality network connectivity is similarly insufficient if the sensor signal is poorly selective or vulnerable to drift. The present study therefore supports a more integrated cyber-physical understanding of smart sensing.

The results signal that environmental monitoring is moving from isolated measurement toward distributed situational awareness. A single monitoring station can provide highly accurate information at one location, but a network of nanosensors can reveal spatial variation and detect localized anomalies that may otherwise remain unnoticed. The ability to observe environmental conditions continuously across multiple points creates a richer representation of exposure patterns and supports more timely intervention.

The earlier warning produced by combined environmental and structural measurements signals that infrastructure deterioration should be interpreted as an interaction between asset condition and surrounding exposure. Corrosion, moisture penetration, thermal variation, and pollutant accumulation do not occur independently of structural behavior. Their combined analysis can reveal deterioration mechanisms before conventional structural thresholds are exceeded. This finding suggests that future infrastructure monitoring should incorporate exposure intelligence as an essential component of condition assessment.

The importance of buffering, edge processing, and communication reliability signals that smart sensing is fundamentally a system-engineering problem rather than only a sensor-development problem. A highly sensitive nanosensor cannot support management decisions when its measurements are lost, delayed, or transmitted inconsistently. Reliable monitoring therefore requires balance among material sensitivity, electronics, communication, computing, and data interpretation. The strongest innovation emerges from integration rather than from maximizing one technological component.

The relationship between sensor drift and declining classification accuracy signals that long-term reliability remains a central challenge. Nanomaterial-based sensors can provide excellent sensitivity while also being affected by surface contamination, environmental interference, aging, and calibration changes. Smart monitoring systems must therefore include mechanisms for recalibration, drift detection, redundancy, and sensor-health assessment. Precision monitoring should be understood as a dynamic condition that requires continual verification rather than as a permanent characteristic established during initial calibration.

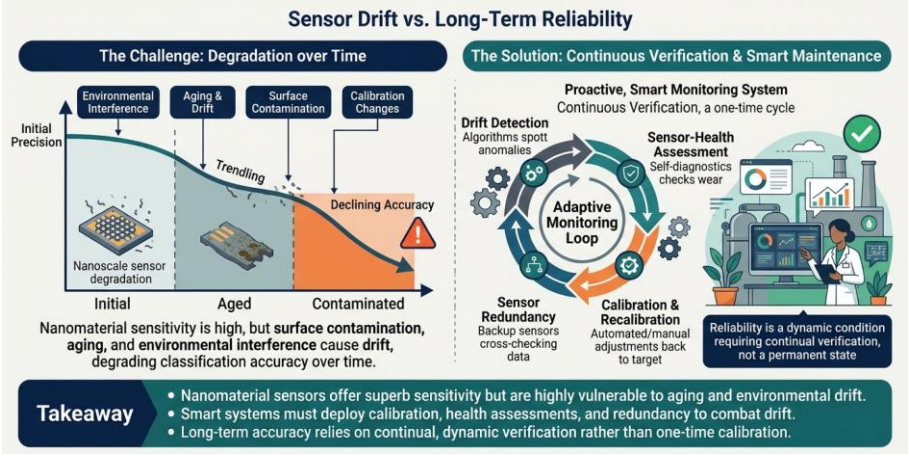


Figure 2. Dynamic Verification: Overcoming Sensor Drift for Long-Term Reliability

The primary environmental implication is that distributed nanomaterial-based networks can strengthen early detection of localized pollution and other environmental anomalies. Rapid sensing combined with spatially distributed nodes can provide higher temporal and spatial resolution than periodic manual sampling or sparse fixed stations. Environmental authorities could use such systems to identify emerging hotspots, monitor short-duration exposure events, and prioritize field verification or mitigation actions more effectively.

The infrastructure-management implication concerns the transition from scheduled inspection toward condition-informed and predictive maintenance. Continuous monitoring enables deterioration signals to be detected before visible failure occurs or before conventional inspection cycles identify the problem. Maintenance decisions can therefore be prioritized according to observed exposure and structural response rather than fixed time intervals. Such an approach may reduce unnecessary intervention while directing resources toward assets showing credible evidence of emerging risk.

The technological implication concerns the need for integrated architecture design. Sensor materials, node electronics, communication protocols, edge computing, and analytical algorithms should be designed as mutually dependent components rather than developed independently (Faqir et al., 2024; Selwal et al., 2025). Energy efficiency becomes particularly important for large-scale deployments because frequent transmission can shorten node lifetime. Edge filtering and event-triggered communication offer practical strategies for maintaining monitoring quality while reducing power consumption.

The governance implication concerns data credibility and decision accountability. Environmental alerts and maintenance recommendations derived from smart sensor networks can influence public safety and resource allocation, making calibration quality, data provenance, and algorithmic transparency essential. Decision makers need to understand whether an alert reflects a confirmed physical change, a sensor fault, or an uncertain classification. Smart infrastructure management therefore requires technical performance standards together with clear procedures for validation, escalation, and human review.

The strong sensing performance can be explained by the physicochemical characteristics of the selected nanomaterials. Graphene and carbon nanotubes provide large active surface areas and highly responsive conductive pathways, allowing small environmental or mechanical changes to generate measurable electrical variations. Metal-oxide nanostructures similarly exhibit strong interactions with humidity and temperature-related surface processes. Functional nanocomposites can combine sensitivity with mechanical or chemical selectivity when their composition is appropriately designed.

The differences in response time can be explained by the nature of the monitored phenomena. Gas adsorption and temperature changes can occur rapidly at the sensor surface, producing short response times. Corrosion-related processes evolve through electrochemical reactions, moisture accumulation, and material degradation that develop more slowly. Sensor-response speed should therefore be interpreted relative to the physics of the target process rather than compared without context.

The communication-performance differences can be explained by distance, signal attenuation, environmental interference, and retransmission requirements. Peripheral nodes experienced greater packet loss because weaker wireless signals increased the probability of unsuccessful transmission. Local buffering reduced the consequences of these interruptions by storing data until communication was restored. Edge processing further improved efficiency because only meaningful or processed information needed to be transmitted continuously.

The success of multivariable anomaly detection can be explained by the complementary information provided by different sensors. A rise in humidity may be harmless when considered alone, while the same increase becomes more significant when accompanied by corrosion activity and abnormal strain behavior. Data fusion allows the analytical system to distinguish isolated environmental variation from patterns associated with actual deterioration.

The improved warning performance therefore reflects the transition from single-variable threshold detection toward contextual condition assessment.

Future research should evaluate the sensor network over substantially longer field deployments. Laboratory and semi-realistic testing can demonstrate technical feasibility, but long-term exposure is necessary to assess sensor drift, fouling, material aging, communication stability, battery degradation, and seasonal environmental effects. Multi-month or multi-year monitoring would provide stronger evidence regarding durability and calibration requirements.

Future investigations should improve nanosensor selectivity under complex environmental conditions. Real-world environments contain multiple gases, humidity fluctuations, temperature variations, particles, and chemical interferents that can influence sensor response simultaneously. Advanced functionalization, sensor arrays, pattern-recognition techniques, and compensation algorithms could help distinguish target substances from background interference. Such developments would reduce false alarms and improve confidence in environmental classifications.

Future studies should advance energy-autonomous network architectures. Solar harvesting, vibration-based energy generation, thermal energy harvesting, and ultra-low-power electronics could reduce dependence on battery replacement in large or inaccessible infrastructure networks. Adaptive sampling and event-triggered transmission should also be examined as strategies for balancing data resolution with long-term energy efficiency. Sustainable power management will become increasingly important as sensor deployments scale to hundreds or thousands of nodes.

Future research should integrate artificial intelligence more deeply with edge and distributed computing. Machine-learning models could identify complex deterioration patterns, sensor faults, environmental anomalies, and emerging correlations across multiple locations. Lightweight models executed at the node or gateway level could reduce latency and network traffic while preserving rapid local response. Model interpretability should remain a priority when analytical outputs are used to support infrastructure safety decisions.

Future implementation should investigate cybersecurity, privacy, and network resilience. Distributed sensing systems can become vulnerable to data manipulation, unauthorized access, node spoofing, communication disruption, and false-data injection. Environmental and infrastructure decisions based on compromised information could generate serious consequences. Secure authentication, encrypted communication, anomaly detection for network behavior, and redundant validation mechanisms should therefore become part of smart sensor-network design.

Future development should ultimately move toward adaptive sensing ecosystems in which environmental measurements, infrastructure conditions, communication quality, and sensor health are evaluated simultaneously. Such systems could automatically recalibrate uncertain nodes, change sampling frequency according to risk, redistribute communication routes, and adjust analytical thresholds when environmental conditions change. The long-term contribution of nanomaterial-based smart sensor networks will depend not simply on achieving higher sensitivity, but on creating reliable, self-aware, energy-efficient, and decision-relevant monitoring systems capable of supporting intelligent infrastructure and environmental management at scale.

CONCLUSION

The most important finding of this study is that the effectiveness of nanomaterial-based smart sensor networks depends not only on sensor sensitivity but on the integration of sensing performance, communication reliability, edge processing, analytical intelligence, and management response. The developed system demonstrated strong measurement accuracy, high packet-delivery performance, reliable anomaly detection, and improved infrastructure-

condition assessment under controlled and semi-realistic conditions. The most distinctive result emerged from multivariable interpretation, where combined environmental and structural measurements produced earlier and more meaningful warnings than isolated sensor thresholds. Humidity, corrosion, strain, pollutant concentration, and communication quality provided complementary information that strengthened condition assessment. These findings indicate that high-performance nanomaterials become practically valuable when their signals are embedded within an integrated cyber-physical monitoring architecture capable of transforming distributed observations into timely environmental alerts and predictive infrastructure-management decisions.

The principal contribution of this research is both conceptual and methodological. Conceptually, the study introduces a multi-layer smart sensing framework that links nanomaterial sensing, wireless communication, intelligent analytics, and management response within a unified environmental–infrastructure monitoring system. This framework advances beyond conventional approaches that treat nanosensors as independent measurement devices or sensor networks as generic communication platforms. Methodologically, the Design Science Research approach integrates nanomaterial characterization, laboratory calibration, network testing, edge processing, anomaly detection, environmental–structural relationship analysis, and iterative prototype refinement. The inclusion of sensor-level, network-level, and management-level performance indicators provides a more comprehensive evaluation model than assessing accuracy or sensitivity alone. The research therefore contributes a practical pathway for translating nanoscale sensing capabilities into system-level intelligence for environmental surveillance and proactive infrastructure management.

The main limitations of this study arise from the prototype-scale deployment, relatively short monitoring period, controlled testing conditions, limited diversity of environmental contaminants, and restricted representation of real infrastructure environments. Long-term sensor drift, fouling, fabrication variability, battery degradation, wireless interference, cybersecurity risks, and changing seasonal conditions were not fully captured. The analytical models were also evaluated using predefined monitoring scenarios rather than prolonged real-world deterioration processes. Future research should therefore conduct multi-season and multi-site field deployments, improve nanosensor selectivity under complex environmental interference, integrate self-calibration and sensor-health diagnostics, and develop energy-harvesting mechanisms for autonomous operation. Further studies should also investigate interpretable artificial intelligence, secure edge computing, adaptive communication protocols, and large-scale integration with digital twins or smart-city platforms to determine whether the proposed architecture can remain reliable, scalable, energy-efficient, and decision-relevant under realistic infrastructure-management conditions.

DECLARATION OF AI AND AI ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work, the author(s) used ChatGPT and QuillBot solely to assist with text translation. After using these tools/services, the author(s) reviewed and edited the content as needed and take full responsibility for the content of the publication.

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.

Author 2: Conceptualization; Data curation; In-vestigation.

Author 3: Data curation; Investigation.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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