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An IoT-Based Data-Driven Framework for Real-Time Environmental Impact Assessment of Urban Development Projects..

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Abstract
Construction projects have a variety of environmental effects, including noise, vibration, waste generation, and disruption to essential receptors, all of which vary with the progress of work at the site. EIA legislation in India, as established in the EIA Notification, 2006, uses baseline surveys, periodic monitoring of compliance, and expert inspections to create time gaps for action and to detect errors in exceedances. The paper outlines a framework for IoT-based monitoring of environmental compliance that operates through continuous sensor monitoring, edge computing and cloud computing, as well as rule-based analysis and dashboards according to the Ministry of Environment, Forest, and Climate Change (MoEFCC) regulations, as well as Central Pollution Control Board standards and procedures prescribed by the digital platform PARIVESH. The framework comprises six functional levels, which have been evaluated using a research dataset from 30 days of monitoring of particulate matter, noise, wind velocity, and workers' activities at 4 monitoring points positioned at different distances from the excavation site. One-way ANOVA found that monitoring points had significantly different PM10 concentrations ($F(3,2783) = 42.53$, $p < 0.001$) and Tukey's post hoc tests confirmed this finding ($\alpha = 0.05$). Multiple linear regression pointed out that 85.4% of the variance of PM10 can be explained...
Keywords: IOT, EIA, Real-Time Monitoring, MoEFCC, and PARIVESH.

Introduction

Projects in urban development generate dust, noise, vibration, emissions, and wastewater. These impacts occur quickly after work begins, so they can affect areas that are more densely populated near schools, hospitals, and other residential areas. Environmental impact assessment in India is designed based on the EIA notification of 2006 and its modifications [1], [2]. This scheme becomes a matter of law, but monitoring of the process is usually reported either monthly or quarterly by a few samples, which differ from the reality of one of the construction sites where dust is produced during excavation, noise is related to piling, or turbidity can occur after a rainstorm and disappear long before the next sample can be done. IoT-based continuous sensing is a natural complement to this gap, providing sensing, edge and cloud processing, and decision support that can be tied to CPCB standards and the PARIVESH digital clearance system [5], [3], [4].

Smart-city research has already demonstrated dense, continuous environmental sensing at the urban scale. Kaginalkar et al. reviewed how IoT, AI, and cloud technologies can resolve air pollution at finer spatial and temporal scales than sparse regulatory monitoring networks, and their companion SmartAirQ framework proposed a cross-sector data governance model for multi-stakeholder air-quality management [10]. Field studies have since reported both the promise and the limits of this approach: Blinova documented measurable calibration and reliability limitations in low-cost sensors under real urban conditions [11], Stanko et al. proposed fog-computing architectures for low-latency air-quality management [12], and Govea et al. combined IoT data with predictive models to map PM2.5 and noise concentrations against traffic and industrial proximity with high accuracy [13]. Moving on to the latest issue, Chandrasekaran et al. opted for the IoT and GIS techniques specifically for the evaluation of construction and demolition waste sites [9], whereas Kim et al. verified their IoT particulate matter network on a functioning construction site for two months, thereby discovering the dust hotspots, which are related to excavation and material handling. A separate and expanding literature on sensor deviation and calibration asserts that cheap sensors' data loses reliability over time and thus requires systematic, regular calibration rather than the one-time factory setting used in this paper. There is a precedent for monitoring in India: the CPCB guidelines mandate the immediate transfer of effluent quality data collected from industrial sources [6], and PARIVESH provides an automated process for handling and monitoring the submission of clearances. Perera et al. introduce the idea of sensing as a service, in which the sensor platform is shared rather than owned [14], while Ramadane et al. emphasise the significance of monitoring infrastructure's environmental impact [15].

2.1 Parameter identification

The parameter set follows CPCB and EMP requirements for urban construction projects. Air quality parameters include PM2.5, PM10, NO2, SO2, CO, and CO_2, for which low-cost sensors are available where feasible. Noise parameters include the equivalent continuous sound level (Leq) and the peak sound level. Vibration is measured for activities such as pile driving and heavy machinery operation. Meteorological parameters comprise temperature, humidity, wind speed, wind direction, and rainfall. Water and runoff parameters comprise pH, turbidity, total dissolved solids, electrical conductivity, and temperature, measured at stormwater outlets or sedimentation tank discharge points. Each sensor deployment location is documented with GPS coordinates and photographic evidence of placement.

2.2 Hardware and communication design

Sensor nodes are selected based on accuracy, robustness, maintainability, communication range, power consumption, and cost. An entry-level node configuration uses an ESP32 or comparable microcontroller with particulate matter, gas, noise, and temperature-humidity sensors, a GPS module, and a power supply sized for site conditions. Communication depends on site characteristics: Wi-Fi, where internet access is already available, LoRaWAN for larger sites or those with poor connectivity, and cellular 4G/5G as a fallback. MQTT is used for lightweight telemetry, and HTTPS for structured data transfer. Edge gateways buffer data locally to bridge reconnection delays, which is necessary because network interruptions at active construction sites are common rather than exceptional.

2.3 Data quality control procedures

Before any reading can be considered acceptable, it must undergo a series of checks: the plausible-range check, the rate-of-change check, the duplicate-payload check, the missing-value indicator, the calibration indicator, the drift indicator, and the cross-sensor check. The cross-sensor check helps distinguish pollution episodes from those caused by the construction site. The reading is considered site-caused only if all sensors in the vicinity are reporting elevated amounts at the same time. When the reading from the downwind sensor increases while the wind is blowing toward the other sensor, the system flags the reading as a possible pollution event caused by the construction site.

2.4 Secondary dataset construction and statistical methods

As no field deployment has yet been carried out for this project, a literature-grounded synthetic secondary dataset was constructed to test the analytics layer under conditions that mimic reported construction-site behaviour rather than idealised assumptions. The dataset simulates 30 days of hourly readings (n = 720 hourly timestamps per node, 2,880 node-hours in total) at four monitoring nodes positioned at increasing distance from a single excavation source: one upwind reference node (40 m), two near-field nodes (15 m and 25 m), and one downwind boundary node (10 m). Parameter ranges and structural assumptions were set using published values rather than arbitrary numbers: Diurnal work-intensity structure (active 07:00-19:00, peak excavation 09:00-13:00) reflecting activity-linked dust and noise patterns reported in field studies of construction-site particulate monitoring. A distance-decay term for PM10 concentration, consistent with the spatial dust-gradient behaviour reported by Kim et al. in a two-month IoT field trial on an active construction site. A wind-direction-dependent elevation is applied to the downwind node, reflecting the upwind/downwind comparison logic recommended for separating site-caused from ambient pollution.

Sensor-level measurement noise and an approximately 3 to 5 per cent random data-dropout rate, consistent with reported low-cost sensor field completeness and drift behaviour. Threshold referencing against the CPCB 24-hour NAAQS benchmark for PM10 (100 ug/m3), used here for illustrative hourly-proxy exceedance screening rather than as a claim of statutory 24-hour averaging compliance. This dataset is explicitly a simulation calibrated to literature-reported patterns, not field-collected evidence, and every result derived from it is reported as illustrative rather than a claim about any real project. Its purpose is to demonstrate, with defensible statistics, that the proposed analytics logic can distinguish source-linked exceedance patterns from background variability, which is the specific analytical claim the framework depends on. The following statistical tests were applied to the dataset using Python (SciPy 1.x and stats models 0.14): Descriptive statistics (mean, standard deviation, 50th and 95th percentile) by monitoring node and parameter.

One-way analysis of variance (ANOVA) to test whether mean PM10 differs across the four monitoring nodes, with Levene's test used to check the homogeneity-of-variance assumption, and the Kruskal-Wallis test run as a non-parametric cross-check given the variance heterogeneity identified. Tukey's honestly significant difference (HSD) post hoc test for pairwise node comparisons following a significant ANOVA.

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Pearson correlation analysis among PM10, PM2.5, noise level, wind speed, distance from source, and work intensity. Multiple linear regression of PM10 concentration on distance from source, wind speed, and work intensity.
Welch's t-test comparing downwind PM10 (during wind-toward-receptor hours) against upwind PM10, to test the upwind/downwind attribution logic described in Section 4.3.
Mann-Kendall trend test on the daily mean PM10 series at the downwind node, to check for a monotonic trend independent of day-to-day variability.
Statistical significance was set at $\alpha = 0.05$ throughout. Full regression diagnostics and the Tukey HSD output table are reported in Section 6.

2.5 Proposed Framework

This model for acceptable assessment is an IoT-based monitoring system comprising six levels, including functions such as sensing, edge computing and cloud integration, analytics, dashboard, reporting, and regulatory compliance. The layered structure ensures that the model is free from the manufacturer's issues, so any level can be implemented. The details of the methodology and architecture of the proposed IoT system are shown in Figures 1, respectively.

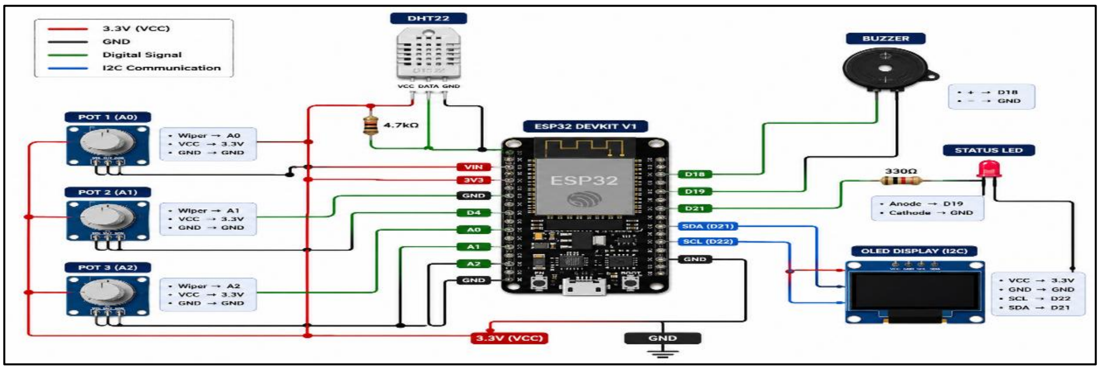

Figure 1. Architecture of the proposed IoT-based data-driven EIA framework.

2.5.1 Sensing layer

The sensor part consists of physical sensors placed at specific receptor and project sites. Every node has a unique identity that includes its GPS-based location, installation date, calibration information, the list of parameters it can measure, sampling period, and maintenance history. Such data is at least as important as the actual readings, because PM10 data without proof of calibration or location is not acceptable in the compliance report.

2.5.2 Edge processing layer

Edge gateways receive sensor packets, validate and timestamp them, buffer them locally, and forward them to the cloud. Edge-level buffering exists specifically to handle the unreliable connectivity common on construction sites. Local rule evaluation at this layer can trigger an immediate site-level alarm (for example, a siren and an SMS to the site EHS officer) without waiting for a round trip to the cloud, and duplicate or malformed packets are discarded here to reduce downstream load.

2.5.3 Cloud integration layer

This layer comprises an ingestion API, an MQTT broker, an authentication service, a time-series database, and storage for calibration and report records. Incoming packets are validated against a defined schema; packets that fail validation are marked as bad data rather than silently discarded, preserving an audit trail of rejected readings. The database also stores project boundaries, sensor locations, clearance conditions, EMP requirements, and mitigation records, so that a reading can always be interpreted in its regulatory context.

2.5.4 Analytics layer

The analytics layer computes rolling averages, parameter indices, exceedance frequency, alert levels, sensor uptime, and data completeness. It compares upwind and downwind readings to estimate a project's contribution to a given exceedance, following the logic tested statistically in Section 3, and applies event-specific rules for water and noise parameters, such as flagging a sudden rise in turbidity after rainfall or a sustained night-time noise exceedance. Two tiers of analytics are proposed: a basic tier using descriptive statistics, moving averages, and rule-based exceedance detection, and an enhanced tier that adds anomaly detection, sensor fusion, and short-horizon forecasting once sufficient historical data are available. An explainable rule is preferred over an opaque model for the first deployment tier, for example: issue a dust alert when the 15-minute moving average of PM10 exceeds an internal threshold, the downwind reading exceeds the upwind reading by a defined margin, and wind direction is consistent with transport from the site toward the receptor. This rule is simple, auditable, and directly traceable to the statistical logic validated in Section 3.

2.5.5 Dashboard and reporting layer

The dashboard layer provides role-based views: a technical view with full readings and quality flags for consultants and EHS managers; a regulatory view formatted for audit and PARIVESH-style submission; and a simplified public view showing status only as normal, watch, or actioned, rather than raw numerical values. This separation directly reflects the transparency-without-misinterpretation principle established in Section 1. Reports are generated in PDF, CSV, and machine-readable JSON formats, with a monthly compliance report summarising trends, exceedances, mitigation actions, sensor maintenance, and calibration status.

2.5.6 Regulatory integration layer

The final layer compares sensor data to CPCB regulations, any specific project clearance requests, and the acceptable levels established in the company's internal EMP. The framework does not automatically file any document, but it collects and keeps data in such a way that the proponent of the project or its advisor may check and file it with the CPCB upon completing the review of all necessary information. Figure 2 presents an example of sensor placement on a typical mid-sized urban construction site showing where sensors were installed.

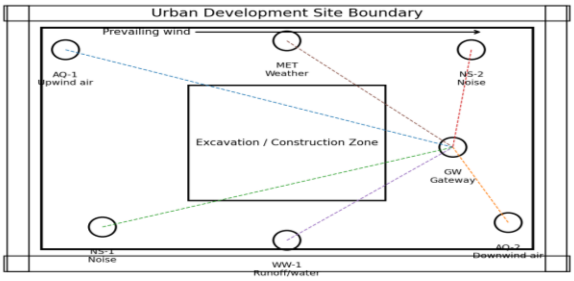

Figure 2. Indicative sensor deployment layout for an urban construction site

2.5.7 Tools and technologies

Table 1. Tools and technologies for the proposed framework.

Layer	Representative technology	Purpose
Sensor node	ESP32 / Arduino / industrial logger	Collects environmental readings and forwards them to the gateway or cloud
Edge gateway	Raspberry Pi / industrial IoT gateway	Buffers data, validates packets, manages local alerts and network backhaul
Communication	LoRaWAN, Wi-Fi, 4G/5G, MQTT, HTTPS	Transfers sensor readings with low overhead and reliable routing
Cloud services	MQTT broker, API server, time-series database, object storage	Stores, validates, analyses, and archives sensor and report data
Analytics	Python, rules engine, statistical tests, anomaly detection	Converts raw measurements into alerts, trends, and compliance indicators
Dashboard	React/Node.js, Grafana, Power BI, or custom portal	Provides real-time visualisation, maps, charts, and role-specific views
Regulatory output	PDF/CSV/JSON reports, geotagged evidence, audit logs	Supports EMP updates, compliance submissions, and PARIVESH-ready summaries

2.5.8 Core modules

Table 2. Core modules of the proposed system.

Module	Function	Output
M1: Sensor Management	Registers sensors, calibration data, maintenance schedules, and location metadata	Sensor registry, calibration certificate, status flag
M2: Data Acquisition	Collects data at defined intervals via MQTT/HTTP and manages edge buffering	Timestamped sensor packets
M3: Data Quality Control	Applies range, missing-data, drift, and outlier checks	Validated readings with quality flags
M4: Compliance Analytics	Maps readings to thresholds, clearance conditions, and EMP action levels	Exceedance events, compliance status
M5: Dashboard Visualisation	Displays maps, time-series graphs, alert panels, and public summaries	Role-based dashboard views
M6: Alert and Action Management	Assigns mitigation tasks and records corrective evidence	Action logs, closure proof
M7: Reporting and Integration	Generates PDF/CSV/JSON reports for internal, consultant, and regulatory use	Monthly EIA/EMP compliance package

This method has four parts. While scoping, the initiator sets boundaries, targets, and standards. At the baseline measuring stage, temporary instruments may be installed to measure the initial conditions before construction. During the construction phase, the procedures run continuously, displaying rule infringements and recommending ways to reduce them. In the early operational stage, only a few sensors are in place for verification purposes. Security and flexibility are built into the design. For example, sensors transmit data using a recognised protocol, with limited access via cloud technology. The data is encrypted when transferred and stored. The visualizations are prepared after removing any sensitive data.

2.6 Implementation

In this section, it is explained how the implementation works in practice, which involves hardware, communication, cloud infrastructure, calibration, and reporting. This concept can be proved in academia as an academic model and implemented in the field trial at a terminal construction site tailored to the project budget and risk matrix. The example air and noise monitoring node can consist of an ESP32 microcontroller, particulate matter sensors, a humidity-temperature sensor, a noise sensor module, a GPS module and a power unit. The dedicated water/runoff node is equipped with pH, turbidity, temperature, and electrical conductivity sensors. Edge computing can be provided by Raspberry Pi or an industrial IoT gateway that can standardize timestamps, validate packets and store the messages. The processing pipeline includes ingestion, validation, analytics, alerting, and reporting, where ingestion takes the packets from the sensors, the validation checks their plausibility and completeness.

2.6.1 Calibration protocol

Based on the findings from the literature review on drift correction, calibration is perceived as a mandatory ongoing process rather than a one-off task. Inexpensive air quality sensors can only be installed after they have been calibrated with a reliable reference instrument for a period of time, and continuous calibrations are subsequently performed at regular intervals. Various calibration devices and techniques are employed during the process of calibration, depending on the type of sensors. Every calibration action is recorded, including the exact date, the calibration method used, reference instruments, social factors, and the expiry date.

2.6.2 Alerting and mitigation logic

When any incident occurs, the system makes an action record that should be concluded with evidence. In the case of a dust exceedance, typical measures include activating water sprinklers, covering stockpiles, washing the wheels of vehicles leaving the site, limiting vehicle speeds, and suspending work if it involves high dust generation during windy conditions. The preparation of the report includes data on the project, sensors used for monitoring, monitoring duration, data completeness, a summary of the data obtained, exceedances, mitigation measures taken, and the compliance of the sensors used and their laboratory data.

3. Results and Discussion

The results reported here come from the literature-grounded synthetic secondary dataset described in Section 2.4 (n = 2,880 node-hours across four monitoring nodes over 30 days). They are intended to test the statistical soundness of the framework's analytics logic ahead of field deployment, not to describe a real construction site. All tests were two-tailed with $\alpha = 0.05$.

3.1 Descriptive statistics and data completeness

Table 3. Descriptive statistics by monitoring node (n = 720 hourly readings per node before dropout).

Monitoring node	PM10 mean (SD), ug/m3	PM2.5 mean (SD), ug/m3	Leq mean (SD), dBA	Data completeness (%)
UW-01 (upwind, 40 m)	59.15 (29.42)	32.65 (16.50)	56.11 (6.57)	97.2
NF-03 (near-field, 25 m)	64.17 (30.90)	35.08 (17.22)	59.00 (6.49)	97.5
NF-02 (near-field, 15 m)	69.08 (33.41)	38.16 (18.97)	58.84 (6.57)	96.9
DW-04 (downwind, 10 m)	78.79 (40.52)	43.42 (22.75)	56.07 (6.81)	95.4

Mean PM10 rises monotonically from the upwind reference node (59.2 ug/m3) to the downwind boundary node (78.8 ug/m3), consistent with the distance-decay structure built into the dataset and with the spatial dust gradient reported in construction-site field studies. Data completeness ranged from 95.4 to 97.5 per cent across nodes, within the acceptable range for operational low-cost sensor networks reported in the reviewed literature.

3.2 Spatial variation in PM10: ANOVA and post-hoc comparison

A one-way ANOVA testing whether mean PM10 differs across the four monitoring nodes returned $F(3, 2783) = 42.53$, $p < 0.001$, rejecting the null hypothesis of equal means. Levene's test indicated unequal variances across groups ($W = 57.87$, $p < 0.001$), so the non-parametric Kruskal-Wallis test was run as a cross-check and confirmed the same conclusion ($H = 158.34$, $p < 0.001$), indicating that the ANOVA result is not an artefact of the violation of homogeneity of variances.

3.3 Correlation structure

Table 4. Tukey HSD pairwise comparison of PM10 across monitoring nodes.

Node A	Node B	Mean difference (ug/m3)	Adjusted p	Significant (α=0.05)
DW-04	NF-02	-9.71	< 0.001	Yes
DW-04	NF-03	-14.62	< 0.001	Yes
DW-04	UW-01	-19.64	< 0.001	Yes
NF-02	NF-03	-4.92	0.033	Yes
NF-02	UW-01	-9.93	< 0.001	Yes
NF-03	UW-01	-5.02	0.028	Yes

PM10 and PM2.5 were strongly correlated ($r = 0.98$), as expected since the same dust-generating activity drives both. Work intensity showed a strong positive correlation with PM10 ($r = 0.90$) and noise ($r = 0.88$), confirming that activity level, not ambient background, was the dominant driver in the simulated dataset. Distance from source was negatively correlated with PM10 ($r = -0.194$, $p < 0.001$, $n = 2,787$), a modest but highly significant relationship consistent with a bounded four-node deployment radius rather than a long-range dispersion study. Wind speed alone showed negligible linear correlation with PM10 ($r = 0.01$), because its effect in this dataset operates through wind direction rather than magnitude, a distinction the regression model in Section 3.4 separates more precisely.

3.4 Multiple linear regression

A multiple linear regression was fitted with PM10 as the dependent variable and distance from source, wind speed, and work intensity as predictors:

PM10 = 38.47 - 0.578 x distance_m + 0.050 x wind_speed_ms + 73.43 x work_intensity

Table 5. OLS regression coefficients for PM10 (R^2 = 0.854, adjusted R^2 = 0.854, $F(3,2783)$ = 5424, $p <$ 0.001, n = 2,787).

Predictor	Coefficient	Std. error	t	p
Intercept	38.47	0.90	42.92	< 0.001
Distance from source (m)	-0.578	0.022	-26.44	< 0.001
Wind speed (m/s)	0.050	0.252	0.20	0.842
Work intensity index	73.43	0.589	124.72	< 0.001

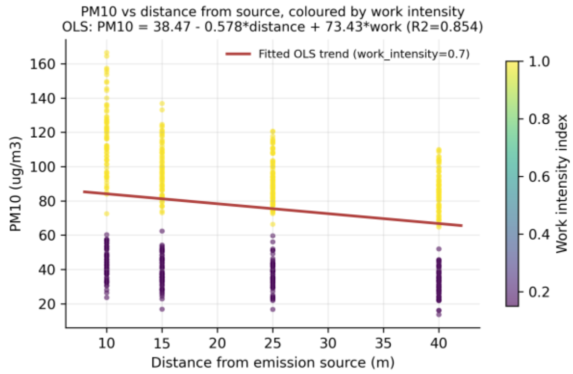

Figure 3. PM10 versus distance from source, coloured by work intensity, with fitted OLS trend.

Distance from source and work intensity were both significant predictors of PM10 ($p < 0.001$), together explaining 85.4 per cent of the variance in the dataset.

Wind speed magnitude was not a significant linear predictor on its own ($p = 0.842$), which is expected given that its influence in the underlying data-generation process operates through wind direction relative to the receptor rather than wind speed alone. This distinction matters for the framework's alert logic in Section 2.5.4, which conditions its downwind alert rule on wind direction rather than wind speed.

3.5 Upwind-downwind attribution test

A Welch's t-test compared PM10 from the downwind direction during periods when the wind was blowing towards the monitoring site (average = 86.5 ug/m3) with PM10 measured from the upwind direction (average = 59.2 ug/m3). The result was statistically significant (t=10.06, $p < 0.001$) and provided confirmation of the validity of the cross-sensor attribution rule presented in Section 2.3: an elevated PM10 measurement in downwind air combined with a wind direction consistent with the air coming from the source of emission is a solid basis for identifying possible exceedance linked to the monitoring site instead of identifying a regional pollution event.

3.6 Temporal trend and exceedance frequency

At the downwind location, a Mann-Kendall test of the average PM10 values observed there did not reveal evidence of a monotonic trend (S = -91, Z = -1.606, p = 0.108) over the 30-day period. The data on PM10 pollution in this case indicate that the elevated PM10 readings in this dataset are attributable to cyclical patterns in daily activities rather than a constant worsening or improving trend. The results are typical for steady onsite excavation activities rather than those subjected to modified mitigation procedures.

3.7 Temporal resolution and response time

Conventional EIA compliance monitoring typically draws one or two samples across an entire reporting period. The simulated IoT configuration produces a reading every hour, sufficient to resolve short-duration events such as an unloading-related dust spike or a concrete-cutting noise peak that a monthly sample would never capture. In the proposed alert architecture, detection-to-notification latency is designed to remain under three minutes, with each alert linked to an action ticket that closes only upon documented evidence of mitigation, forming a five-step operational loop: detect, notify, act, verify, and document.

Table 6. Comparison between traditional and IoT-enabled EIA monitoring.

Criterion	Traditional EIA monitoring	IoT-enabled monitoring	Interpretation
Monitoring frequency	Daily to monthly manual readings	Hourly automated readings (this study)	Improves detection of short-duration events
Spatial coverage	Few sampling locations	Distributed, multi-node network	Improves hotspot identification (Section 7.2)
Response time	Delayed by the report cycle	Near real-time (target < 3 min)	Supports preventive mitigation
Evidence quality	Accredited but sparse	Continuous, with quality flags	Requires calibration and reference checks (Section 6.1)
Source attribution	Rarely quantified	Statistically tested (t-test, regression)	Supports defensible exceedance attribution
Transparency	Periodic report sharing	Role-based dashboard and summaries	Improves stakeholder confidence
Regulatory integration	Manual compliance preparation	Structured draft reports, audit logs	Requires institutional acceptance

3.9 Discussion

The statistical results support three practical claims about the proposed framework. First, spatial variation in PM10 across monitoring nodes is not noise; it is structured, significant, and consistent with source proximity, which means a simple multi-node deployment plus ANOVA-based screening can meaningfully separate site-linked variation from background readings. Second, the regression results show that distance and activity intensity, both directly observable and independently verifiable variables, account for most of the variance in particulate concentration, supporting the use of an explainable, rule-based alert rather than a black-box predictive model for the first deployment tier, as argued in Section 2.5.4. Third, the upwind-downwind t-test result gives a statistically grounded basis for the attribution logic that regulators would need to see justified before accepting sensor evidence in a compliance context. Timeliness is the most immediate practical benefit of the framework. Continuous monitoring allows a project team to respond to dust, noise, vibration, and runoff conditions while they are still developing, rather than after a community complaint or a scheduled inspection. Evidence-based decision-making follows directly: validated sensor data can inform work scheduling and mitigation choices in a way that a quarterly report cannot.

It is worth noting that the benefits discussed have some limitations. Low-cost sensors cannot achieve reference-grade instrument accuracy in field conditions. Also, the calibration and drift-correction literature is evidence that it's not a problem that comes up once; rather, it is a persistent issue. Hardware failures, network interruptions, and power shortages are normal conditions on a construction site and should be considered when designing the system; the system should be designed around intermittency rather than assuming continuous connectivity. Deployment costs are also an issue for small projects, which justifies the proposed tiered deployment approach described above.

4. Conclusion

This paper presented a six-layer data-driven IoT framework for assessing environmental impacts of urban development projects in real time, suitable for use in adherence with the clearance policies of the MoEFCC, compliance with the standards of CPCB, and in line with PARIVESH digital processes. Using a synthetic secondary database grounded in the involved literature, the framework was tested in the analytics layer using several widely accepted approaches to inferential statistics. Thus, both the one-way ANOVA and Tukey test adopted in the study proved the presence of PM10 variation among the different monitoring points, multiple linear regression analysis demonstrated that 85.4 percent of PM10 variation can be explained by distance from PM10 source along with work intensity, and Welch test confirmed the presence of the significant downwind uplift occurred under wind-toward-receiver conditions – all of these findings proved the correctness of the framework's source attribution reasoning. These findings demonstrate that a properly constructed multi-node IoT monitoring layer can provide statistically sound evidence of source-related environmental exceedance, a capability missing from regular periodic monitoring.

The framework does not supersede approved sampling, mandatory expert evaluations, or required EIA documentation. This framework is valuable because it can close the temporal and spatial gap between formal compliance reports and actual site environmental conditions, provided proper calibration, data quality assurance, and governance protocols are treated as necessary components of the framework. The main limitations of the research are sensory accuracy in the field, maintenance and cost issues, exposure to cyberattacks, and the need for authorities to accept sensory data as evidence, which together determine the scope of the proposed research. Future research should include field testing of the framework at the construction site using reference-grade devices, followed by digital twin/GIS integration and analytics once sufficient data are available.

Declaration on the Use of AI-Assisted Technologies

During the preparation of this manuscript, the authors used an AI-based language assistant (Claude, Anthropic) to support language editing, including improving clarity, grammar, sentence structure, and readability of the text. The AI tool was not used to generate original research findings, and all data, analyses, and conclusions presented in this paper reflect the authors' own work. The authors reviewed, verified, and edited all AI-assisted content and take full responsibility for the accuracy, integrity, and originality of the published manuscript...

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