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**Sustainability Data Management Platform for Industry**

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Peer Review Information	Abstract
<p><i>Submission: 16 March 2026</i></p> <p><i>Revision: 03 April 2026</i></p> <p><i>Acceptance: 26 April 2026</i></p> <p><b>Keywords</b></p> <p><i>Sustainability, Air Quality Index, Carbon Emissions, Energy Monitoring, Django REST Framework, Hybrid Intelligent System, Rule-Based Reasoning, Environmental Data Management, Industrial IoT, Role-Based Access Control.</i></p>	<p>Rapid industrialization has intensified environmental degradation, making systematic monitoring of ecological indicators indispensable for regulatory compliance and sustainable development. This paper presents the Sustainability Data Management Platform (SDMP), a web-based system designed to monitor and manage environmental sustainability data in industrial settings. The platform tracks critical parameters including the Air Quality Index (AQI) based on Central Pollution Control Board (CPCB) standards, carbon dioxide emissions derived from established emission factor formulas, energy consumption, and fuel usage. Built on a three-tier architecture employing React on the frontend, Python Django with Django REST Framework on the backend, and PostgreSQL as the persistent data store, the system incorporates a hybrid intelligent approach that combines rule-based threshold detection with pattern-based recommendation logic. An alert classification mechanism categorizes operational states as Safe, Warning, or Critical, while a structured recommendation engine generates actionable insights in the form of Problem–Action–Impact triplets. A role-based workflow spanning Data Entry Operator, Analyst, Manager, Supervisor, and Administrator roles ensures data integrity and governance. Evaluation on a simulated industrial dataset demonstrates that the platform reliably detects threshold violations, produces contextually relevant recommendations, and presents environmental trends through interactive dashboards. The SDMP offers a pragmatic and scalable foundation for industrial sustainability management, without reliance on computationally intensive machine learning models.</p>

**Introduction**

The accelerating pace of industrial activity has emerged as one of the principal drivers of environmental deterioration worldwide. Particulate matter, greenhouse gas emissions, and unsustainable energy practices collectively contribute to climate change, public health deterioration, and ecosystem disruption [1]. In response, regulatory bodies such as the Central Pollution Control Board (CPCB) in India have established binding standards for air quality and industrial effluents, mandating industries to

monitor and report environmental parameters on a continuous basis [2].

Despite the existence of such mandates, many small and medium-scale industries continue to rely on fragmented, spreadsheet-based record-keeping that is both error-prone and difficult to audit. The lack of real-time monitoring and actionable intelligence further impedes timely corrective interventions. Consequently, there is a pressing need for integrated digital platforms capable of aggregating environmental data, computing standardised indices, and generating

interpretable guidance for operational decision-making.

This paper introduces the Sustainability Data Management Platform (SDMP), a full-stack web application engineered to address these deficiencies. The SDMP consolidates four key environmental dimensions—air quality, carbon emissions, energy consumption, and fuel usage—into a unified dashboard accessible to multiple organizational roles. Rather than deploying computationally intensive deep learning models, the system adopts a hybrid intelligent approach that pairs deterministic rule-based threshold evaluation with pattern-based heuristic reasoning. This design choice enhances interpretability and reduces the computational overhead associated with data-sparse industrial environments.

The primary contributions of this work are as follows:

1. A modular, three-tier web architecture for industrial environmental data management.
2. An AQI computation engine conforming to CPCB sub-index standards.
3. A carbon emission calculation module based on internationally recognised emission factor methodology.
4. A hybrid intelligent recommendation system producing structured Problem–Action–Impact outputs.
5. A multi-tier role-based access control workflow ensuring data governance.
6. Evaluation of the platform against a simulated industrial dataset.

## Literature Review

Research on environmental monitoring systems has evolved considerably over the past decade, transitioning from simple sensor networks to sophisticated data-driven platforms. A review of related work reveals several thematic clusters pertinent to the design of SDMP.

### 1. IoT-Enabled Environmental Monitoring

Kumar et al. [3] demonstrated the feasibility of low-cost sensor arrays for urban AQI monitoring, noting that web-based dashboards significantly improve the accessibility of collected data. Similarly, Patel and Sharma [4] deployed a Raspberry Pi-based monitoring system for industrial premises and reported that real-time alerts reduced response latency by up to 35%. However, these implementations lacked structured recommendation logic and multi-role governance, limiting their applicability to larger organisational contexts.

### 2. Carbon Emission Calculation Methods

The Intergovernmental Panel on Climate Change (IPCC) Tier 1 methodology employs activity data multiplied by emission factors to estimate greenhouse gas outputs [5]. Several software tools, including GHG Protocol-compliant calculators, have operationalised this approach for industrial inventories. The SDMP adopts this established methodology, ensuring that computed emission values are aligned with internationally recognised accounting standards.

### 3. Rule-Based and Expert Systems for Environmental Decision Support

Hybrid intelligent systems combining rule-based engines with pattern-recognition heuristics have been applied effectively in domains where labelled training data are scarce. Chen et al. [6] proposed a fuzzy rule-based system for environmental impact assessment that outperformed naive threshold detectors on recall while remaining interpretable to domain experts. Gupta and Mishra [7] applied a similar approach to energy management in manufacturing, demonstrating that structured recommendation outputs reduced energy waste by 18% in pilot facilities. These findings informed the design of SDMP's recommendation engine.

### 4. Web-Based Environmental Management Platforms

Commercial platforms such as Enablon and Intelex offer comprehensive environmental, health, and safety (EHS) management suites; however, their proprietary nature and licensing costs render them inaccessible to many industries in developing economies [8]. Open-source alternatives remain fragmented and poorly maintained. SDMP addresses this gap by providing an open, extensible platform grounded in modern web technologies.

### 5. Role-Based Access Control in Industrial Information Systems

The importance of granular access control in industrial data systems is well-documented. Sandhu et al. [9] formalised the Role-Based Access Control (RBAC) model, and subsequent work by Ferraiolo et al. [10] established its suitability for complex organisational hierarchies. SDMP implements a five-tier RBAC model that mirrors the approval workflow common in industrial quality-management systems.

## Methodology

### 1. Data Collection

Given that SDMP is a prototype platform, evaluation relies on a simulated industrial dataset generated to reflect realistic operational conditions of a mid-scale manufacturing facility. The dataset encompasses 90 days of daily records for the following parameters:

**Table 1:** Simulated Dataset Parameters

Parameter	Unit	Simulated Range	Source Basis
PM2.5 concentration	$\mu\text{g}/\text{m}^3$	15 – 250	CPCB ambient standards
PM10 concentration	$\mu\text{g}/\text{m}^3$	30 – 450	CPCB ambient standards
NO <sub>2</sub> concentration	$\mu\text{g}/\text{m}^3$	10 – 200	CPCB ambient standards
SO <sub>2</sub> concentration	$\mu\text{g}/\text{m}^3$	5 – 150	CPCB ambient standards
CO concentration	$\text{mg}/\text{m}^3$	0.5 – 10	CPCB ambient standards
Diesel consumption	Litres/day	200 – 800	Industry benchmark
Coal consumption	kg/day	500 – 3000	Industry benchmark
Electricity consumption	kWh/day	500 – 5000	Industry benchmark

Data entry is performed through the platform's web interface by authorised Data Entry Operators and subsequently reviewed through a multi-stage approval workflow before being stored in the PostgreSQL database.

## 2. Air Quality Index Calculation

The platform computes AQI in accordance with the methodology prescribed by the Central

Pollution Control Board of India [2]. Sub-indices are computed for each pollutant using linear interpolation between breakpoints defined in the CPCB standard, and the overall AQI is the maximum of the individual sub-indices.

For a pollutant with measured concentration  $C_p$ , the sub-index  $I_p$  is given by:

$$I_p = [(I_{Hi} - I_{Lo}) / (BPHi - BPLo)] \times (C_p - BPLo) + I_{Lo}$$

**Table 2:** AQI Sub-Index Formula Symbols

Symbol	Definition
$I_p$	Sub-index for pollutant p
$C_p$	Measured concentration of pollutant p
$BPHi$	Breakpoint concentration $\geq C_p$
$BPLo$	Breakpoint concentration $\leq C_p$
$I_{Hi}$	AQI value corresponding to $BPHi$
$I_{Lo}$	AQI value corresponding to $BPLo$

The composite AQI is then:

$$AQI = \max(IPM2.5, IPM10, INO_2, ISO_2, ICO)$$

approach [5]. For each fuel type, CO<sub>2</sub>e emissions are computed as:

$$E = AD \times EF \times GWP$$

## 3. Carbon Emission Calculation

Carbon dioxide equivalent emissions are estimated using the IPCC Tier 1 emission factor

**Table 3:** Carbon Emission Formula Symbols

Symbol	Definition	Example Value
$E$	CO <sub>2</sub> equivalent emissions (kg CO <sub>2</sub> e)	—
$AD$	Activity data (quantity of fuel consumed)	500 L diesel/day
$EF$	Emission factor (kg CO <sub>2</sub> e per unit of fuel)	2.68 kg CO <sub>2</sub> e/L
$GWP$	Global Warming Potential (dimensionless)	1 for CO <sub>2</sub>

Total daily facility emissions are the sum of contributions from all fuel types: diesel, coal, and grid electricity. The grid electricity emission factor is sourced from the Ministry of Power's CO<sub>2</sub> Baseline Database for the Indian Power Sector.

## 4. Hybrid Intelligent Agent Design

The intelligence layer of SDMP deliberately avoids deep learning or heavy machine learning techniques, which require substantial historical labelled data and lack transparency for domain

users. Instead, a hybrid intelligent approach is adopted, combining two complementary reasoning strategies.

**Rule-Based Threshold Detection:**

Each monitored parameter is associated with configurable threshold bands derived from regulatory standards and engineering heuristics. The system classifies each daily record into one of three alert states:

**Table 4: Alert Classification Thresholds**

Alert Level	AQI Range	Emission Baseline	vs.	Action Triggered
Safe (Green)	0 – 100	< 90%		Log only
Warning (Amber)	101 – 200	90% – 120%		Notify Analyst
Critical (Red)	> 200	> 120%		Escalate to Manager

**Pattern-Based Recommendation Logic:**

When threshold violations are detected, the recommendation engine analyses contextual patterns—such as sustained multi-day exceedances, co-occurrence of high AQI with elevated fuel consumption, or anomalous spikes relative to a rolling seven-day average—and maps them to a curated knowledge base of intervention strategies. Each recommendation is structured as a Problem–Action–Impact triplet:

**Problem:** A concise statement of the detected anomaly.

**Action:** A specific, operationally feasible corrective measure.

**Impact:** The anticipated environmental or operational benefit.

This structured output format was selected to align with standard environmental management workflows, where corrective action requests must document justification and anticipated outcomes.

**System Design**

**1. Three-Tier Architecture**

SDMP adheres to a classical three-tier client-server architecture that segregates presentation, application logic, and data persistence, facilitating independent scaling and maintenance of each layer.

**Table 5: Three-Tier Architecture Components**

Tier	Technology Stack	Responsibility
Presentation Tier	React (with Lovable.dev scaffolding), Recharts, Tailwind CSS	User interface, dashboard visualisations, form handling
Application Tier	Python 3.11, Django 4.x, Django REST Framework, JWT	Business logic, AQI/emission computation, recommendation engine, API endpoints
Data Tier	PostgreSQL 15	Persistent storage of environmental records, user profiles, roles, recommendations

Communication between the presentation and application tiers is conducted exclusively via RESTful API calls over HTTPS, with JSON as the interchange format. Stateless authentication is enforced using JSON Web Tokens (JWT),

eliminating server-side session management and enabling horizontal scalability.

**2. Data Flow**

The end-to-end data flow within SDMP proceeds through the following stages:

**Table 6: End-to-End Data Flow Stages**

Stage	Description
Data Entry	The Data Entry Operator logs environmental readings (pollutant concentrations, fuel quantities, energy units) via the React frontend. Client-side validation checks for range plausibility and mandatory field completion before submission.

<b>API Transmission</b>	Validated data is serialised as JSON and transmitted to the Django REST Framework backend via an authenticated POST request carrying a JWT bearer token.
<b>Server-Side Validation &amp; Computation</b>	The backend deserialises and validates the payload using DRF serialisers, then invokes the AQI computation module and emission calculation module to derive derived metrics.
<b>Alert Classification</b>	The alert classification service evaluates computed metrics against threshold bands and assigns a Safe, Warning, or Critical alert state to each record.
<b>Recommendation Generation</b>	If a Warning or Critical state is detected, the recommendation engine performs contextual pattern analysis and generates a Problem–Action–Impact triplet, which is persisted alongside the primary record.
<b>Approval Workflow</b>	The record enters the role-based approval queue: Analyst reviews accuracy, Manager approves operational actions, Supervisor authorises escalations, and Admin oversees the full audit trail.
<b>Data Persistence</b>	Approved records and recommendations are committed to PostgreSQL.
<b>Dashboard Rendering</b>	The React frontend polls the API for aggregated metrics and renders time-series charts, AQI gauges, emission summaries, and alert feeds using Recharts visualisation components.

### 3. Role-Based Workflow

SDMP implements a five-tier RBAC model that mirrors industrial quality-management approval chains:

**Table 7: Role-Based Access Control Permissions**

<b>Role</b>	<b>Permissions</b>
<b>Data Entry Operator</b>	Submit environmental readings; view own submissions
<b>Analyst</b>	Review and annotate submitted records; view all department data; access analytical dashboards
<b>Manager</b>	Approve or reject Analyst-reviewed records; view facility-wide dashboards; receive Warning alerts
<b>Supervisor</b>	Override Manager decisions; access cross-facility comparisons; receive Critical alerts
<b>Administrator</b>	Full system access including user management, threshold configuration, and audit log inspection

### Implementation

#### 1. Backend Implementation

The backend is implemented in Python 3.11 using the Django 4.x framework. Django REST

Framework provides the serialiser and viewset infrastructure for RESTful endpoint exposition. The project is organised into the following Django applications:

**Table 8: Django Application Modules**

<b>Django Application</b>	<b>Responsibility</b>
<i>accounts</i>	Custom user model, JWT authentication endpoints (login, refresh, logout), role assignment
<i>monitoring</i>	Models and API endpoints for AQI records, carbon emission records, energy records, and fuel records

<b><i>intelligence</i></b>	Alert classification service, recommendation engine, and recommendation storage
<b><i>dashboard</i></b>	Aggregation endpoints returning summarised metrics for dashboard rendering
<b><i>workflow</i></b>	Approval state machine, notification service, and audit log

Authentication is managed via the `djangorestframework-simplejwt` library. Access tokens have a 60-minute expiry, after which the client must exchange a refresh token for a new access token. Role-based permission classes restrict endpoint access in accordance with the RBAC model.

The AQI computation module iterates over CPCB breakpoint tables stored in the database, applies the sub-index formula for each pollutant, and returns the composite AQI. The emission calculation module references a fuel-factor lookup table containing IPCC and Ministry of Power emission factors. Both modules are implemented as stateless utility functions invoked synchronously during record creation.

## 2. Frontend Implementation

The frontend is a single-page application (SPA) built with React 18, scaffolded using `Lovable.dev`. State management is handled via React Context API supplemented by React Query for server-state synchronisation and caching. Routing is managed by React Router v6.

The dashboard presents the following primary views:

- **AQI Monitor:** Real-time AQI gauge with colour-coded alert indicator and 30-day trend line chart.
- **Carbon Emissions:** Bar chart of daily CO<sub>2</sub>e emissions with comparison against facility baseline.
- **Energy Consumption:** Area chart with peak-demand annotations.
- **Fuel Analysis:** Stacked bar chart decomposing consumption by fuel type.
- **Alerts Feed:** Chronological list of triggered alerts with severity badges.
- **Recommendations Panel:** Paginated list of Problem–Action–Impact recommendations.

- **Workflow Queue:** Role-specific queue of records pending review or approval.

## 3. Hybrid Intelligent Agent Integration

The recommendation engine is implemented as a Python service class invoked by the Django signal system whenever a monitoring record transitions to Warning or Critical alert state. The engine encapsulates a knowledge base of 24 rule–recommendation mappings organised by parameter domain (AQI, emissions, energy, fuel). Pattern analysis compares the current record against a rolling seven-day window retrieved from the database to distinguish transient spikes from sustained trends, adjusting recommendation priority accordingly. A simplified illustrative rule from the knowledge base is as follows:

IF AQI > 200 AND rolling\_7day\_avg(AQI) > 150  
THEN

Problem : "Sustained critical air quality degradation detected."

Action : "Inspect and service primary filtration units; reduce high-emission process lines by 20% within 48 hours."

Impact : "Projected AQI reduction of 30–50 units within 72 hours."

## Results And Discussion

Evaluation of SDMP was conducted using the 90-day simulated industrial dataset described in Section III-A. The following subsections present the key findings.

### 1. AQI Monitoring

Across the 90-day period, the AQI computation module correctly classified all simulated records against the CPCB standard breakpoint table. Alert states were assigned as follows:

**Table 9:** AQI Alert State Distribution (90-Day Simulation)

Alert Level	Days Recorded	Percentage
Safe (AQI ≤ 100)	41	45.6%
Warning (101–200)	33	36.7%
Critical (> 200)	16	17.8%

The distribution reflects realistic industrial variability. Peak AQI values consistently corresponded with days of elevated coal consumption, validating the expected causal relationship within the simulated dataset.

## 2. Carbon Emission Estimation

Daily CO<sub>2</sub>e emissions ranged from approximately 1,840 kg to 9,720 kg across the simulation period, with diesel and coal accounting for 78% of total estimated emissions. The emission calculation module produced deterministic outputs for each input record, and cross-validation against manual spreadsheet calculations confirmed numerical correctness.

It is important to note that these figures are derived from simulated activity data and should not be interpreted as representative of any specific real-world industrial facility. The primary purpose of this evaluation is to verify the functional correctness of the calculation pipeline.

## 3. Recommendation Engine Performance

The hybrid recommendation engine generated 49 recommendations across the 90-day simulation (33 Warning-level, 16 Critical-level). All 24 knowledge-base rule–recommendation mappings were triggered at least once. Qualitative inspection confirmed that generated Problem–Action–Impact triplets were contextually appropriate for the associated parameter values. No false-positive recommendations were observed for records classified as Safe.

Because the system is not trained on real industry data and does not employ predictive modelling, quantitative metrics such as precision and recall are not applicable. Rather, the evaluation confirms correct rule triggering and recommendation structure integrity.

## 4. Role-Based Workflow

The five-tier approval workflow was exercised through the full 90-day dataset. Record progression through the workflow states (Pending → Analyst Review → Manager Approval → Supervisor Approval → Approved) was verified to enforce role-based permissions correctly. Unauthorised access attempts simulated during testing were rejected with appropriate HTTP 403 responses.

## 5. System Performance

API response times were measured under a simulated load of 20 concurrent users on a development server (Intel Core i5, 8 GB RAM). The median response time for record creation (including AQI computation and recommendation generation) was 148 ms, and the 95th percentile

was 310 ms. Dashboard aggregation endpoints returned responses within 220 ms at the 95th percentile. These figures are considered acceptable for a web-based environmental monitoring application, though production deployment on optimised infrastructure would be expected to yield significantly lower latencies.

## Conclusion And Future Scope

This paper has presented the Sustainability Data Management Platform (SDMP), a web-based environmental monitoring system designed to assist industrial facilities in tracking air quality, carbon emissions, energy consumption, and fuel usage. The platform's three-tier architecture—combining a React frontend, Django REST Framework backend, and PostgreSQL database—provides a modular, maintainable foundation. The hybrid intelligent approach, integrating rule-based threshold detection with pattern-based recommendation logic, delivers actionable Problem–Action–Impact guidance without the data requirements or opacity associated with machine learning techniques. Evaluation against a simulated industrial dataset confirmed the functional correctness of the AQI computation, emission estimation, alert classification, and recommendation generation modules.

SDMP addresses a practical gap in accessible, open environmental data management tooling for small and medium-scale industries, particularly in developing economies where proprietary EHS platforms are cost-prohibitive.

Future development will focus on the following directions:

- **Real-World Dataset Integration:** Deployment in a live industrial setting to validate performance against authentic operational data and refine threshold configurations.
- **IoT Sensor Integration:** Addition of a real-time data ingestion pipeline from IoT-enabled air quality sensors and smart energy meters, eliminating manual data entry.
- **Predictive Analytics Module:** Incorporation of lightweight time-series forecasting models (e.g., ARIMA or exponential smoothing) to provide short-horizon emission and AQI projections.
- **Mobile Application:** Development of a companion mobile application for field operators, supporting offline data entry with synchronisation upon connectivity restoration.
- **Regulatory Report Generation:** Automated generation of compliance reports in formats required by regional pollution control boards.

- Multi-Facility Support: Extension of the data model and RBAC to support enterprise deployments spanning multiple geographically distributed facilities.

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