

AI-Based Carbon Emission Monitoring and Penalty System for Industrial Pollution Control

Suryansh Prasad¹ Aniket Abhimanyu Vishwakarma² Shubham Dhananjay Yadav³ Rishikesh Suresh Kumar Yadav⁴ Jaggumantry Swapna Kumari⁵

^{1,2,3,4}Student ⁵Assistant Professor

^{1,2,3,4,5}Department of Electrical Engineering

^{1,2,3,4,5}Lokmanya Tilak College of Engineering, Kopar Khairane, Navi Mumbai, India

Abstract — Industrial growth has been accompanied by a steady rise in carbon dioxide and other hazardous emissions, with the industrial sector directly responsible for roughly a fifth to a quarter of global greenhouse gas (GHG) emissions. Current emission accounting largely depends on voluntary self-reporting by companies, which is difficult to verify and easy to under-report. This paper proposes a comprehensive framework in which Artificial Intelligence (AI) is used to independently estimate and cross-verify the carbon emissions of individual companies by fusing satellite/remote-sensing data, Internet of Things (IoT)-based continuous emission monitors, and company activity data, following the GHG Protocol's Scope 1/2/3 classification. Based on the verified emission intensity of each company relative to a sector-specific benchmark, a tiered financial penalty is proposed, modelled loosely on existing mechanisms such as the European Union Emissions Trading System and India's Carbon Credit Trading Scheme. The paper further proposes that the computed emission data be compiled into a public annual report released by the government, so that regulators, investors and citizens can hold polluting industries accountable. Experimental simulation indicates a coefficient-of-determination (R^2) cross-verification fidelity, demonstrating strong agreement with the reference data across the evaluated industrial sectors. The framework is intended to make industrial pollution measurement more transparent, harder to falsify, and to create a financial incentive for industries to adopt cleaner technology.

Keywords: Carbon Emission, Industrial Pollution, Artificial Intelligence, Emission Monitoring, Carbon Tax, Environmental Regulation, Penalty Mechanism, MRV (Monitoring, Reporting, Verification)

I. INTRODUCTION

Every industry that manufactures goods, generates power, or processes raw material releases some quantity of carbon dioxide and other hazardous substances into the environment as a by-product of production. As industrial output has grown, particularly in developing economies such as India and China, the volume of these emissions has grown alongside it, contributing directly to climate change, air quality degradation, and public health damage.

At present, emissions accounting in most jurisdictions relies heavily on companies self-reporting their own activity data, which is then converted into estimated emissions using standard factors. This creates two problems: first, self-reported data can be under-reported or falsified without an independent check; second, the resulting data are often not made public in a timely, comparable format that citizens or regulators can act upon.

This paper proposes a system in which Artificial Intelligence (AI) is used to estimate and independently verify how much carbon each company or facility is emitting, using a combination of satellite imagery, Internet of Things (IoT) sensor data and self-reported figures. Once a verified emission figure exists for each company, a financial penalty proportional to the excess emission over a sector benchmark can be charged, and the results can be compiled into a public annual report by the government. The objective is not merely to punish industries, but to create a transparent, continuously verifiable, and financially self-sustaining system that pushes industries toward cleaner production without requiring them to shut down.

II. REVIEW OF LITERATURE

Several mechanisms already attempt to solve parts of this problem. The European Union Emissions Trading System (EU ETS) is the world's largest cap-and-trade carbon market, in which industries are allotted emission allowances and must purchase additional allowances if they exceed them [1]. India's Carbon Credit Trading Scheme (CCTS), notified under the Energy Conservation (Amendment) Act, 2022 and administered by the Bureau of Energy Efficiency, follows a similar logic: obligated entities are given a greenhouse gas emission intensity target, and must buy Carbon Credit Certificates if they exceed it, or may sell certificates if they perform better than the target [2]. This scheme builds on the earlier Perform, Achieve, Trade (PAT) scheme.

On the measurement side, Climate TRACE is an independent international coalition that uses satellite imagery and machine learning to estimate emissions from individual facilities worldwide, entirely independent of company self-reporting, and makes these data publicly available [3]. The Greenhouse Gas (GHG) Protocol provides the globally accepted framework for classifying emissions into Scope 1 (direct), Scope 2 (purchased energy) and Scope 3 (value chain) categories [4], while the Carbon Disclosure Project (CDP) operates a global platform on which companies voluntarily disclose their emissions [5]. More recently, research such as the GREEN framework has explored the use of large language models (LLMs) to estimate a company's emissions from its revenue and sector classification when direct measurement data is unavailable [6].

Framework	Primary Data Source	Verification Mode	Regulatory Penalty
EU ETS [1]	Self-reporting & Third-party audit	Manual periodic verification	Fixed statutory fine per excess tonne
India CCTS [2]	Activity log & Designated Energy Agency	Periodic third-party audit	Carbon credit deficit penalty
Climate TRACE [3]	Satellite / Multispectral imaging	Purely remote ML inference	Nonpunitive public registry
Proposed Framework	Multi-Modal: Satellite + IoT Stack + Activity Logs	Continuous AI cross-check (Bi-LSTM / CNN)	Dynamic tiered penalty + public disclosure

Table I: Comparative Analysis of Emission Monitoring Approaches

As summarized in Table I, existing schemes either rely on periodic manual audits susceptible to reporting bias or offer independent remote sensing without immediate enforcement integration. This paper combines cap-and-trade market logic, satellite-based independent verification, and continuous AI analytics into a closed-loop measurement-and-penalty pipeline.

III. EXTENT OF POLLUTION AND CONTRIBUTING INDUSTRIES

Global data compiled by the EDGAR Community GHG Database places direct industrial combustion and process emissions at approximately 21.5% of total global greenhouse gas emissions (excluding land use change); this share rises to roughly 25-31% once indirect emissions from electricity used by industry are included [7]. Within industry, a small number of sectors dominate: the iron and steel, cement, and chemical sectors together account for around 70-71% of global industrial carbon dioxide emissions [7], [8]. Individually, the steel industry alone produces close to 3 billion tonnes of CO₂ per year, close to 9% of total global CO₂ emissions, while cement production accounts for a further 7-8% of the global total, and aluminium production for close to 0.8% [9]. Considering all sectors together (not only manufacturing industry), the power generation sector is the single largest emitter, responsible for roughly 36-38% of global CO₂ emissions in 2023-24, with coal-based power generation as the dominant contributor [10].

Based on these data, the following industries should be treated as priority sectors for AI-based emission monitoring:

- Thermal power generation (coal, gas and oil-based)
- Iron and steel manufacturing
- Cement and construction materials
- Petrochemicals, fertilizers and chemical manufacturing
- Oil refining and gas processing
- Aluminium and other nonferrous metal smelting
- Pulp, paper and textile/dyeing units
- Large-scale mining operations

IV. ENVIRONMENTAL, HEALTH AND ECONOMIC LOSSES

The damage caused by unchecked industrial emissions is not limited to long-term climate change; it produces measurable, near-term losses. Globally, air pollution was linked to close to 7 million premature deaths in 2019, around 12% of all deaths worldwide [11]. India, where a large share of ambient particulate pollution originates from industrial combustion and coal-based power generation alongside vehicular and household sources, recorded an estimated 1.67 million deaths attributable to air pollution in 2019—about 17.8% of all deaths in the country that year—with an associated economic loss of USD 36.8 billion, equal to roughly 1.36% of national gross domestic product (GDP) [12], [13]. A more recent 2022 estimate that accounts for the broader economic cost of fossil-fuel-related PM2.5 exposure places India's annual loss closer to USD 339 billion, or about 9.5% of GDP, when the full economic burden of premature death and morbidity is counted [14]. Separately, the Reserve Bank of India has projected that lost labour hours from extreme heat and air pollution combined could cost India up to 4.5% of GDP annually by 2030 [15].

Beyond direct health costs, industrial pollution results in:

- Reduced agricultural yield due to ground-level ozone and soil/water contamination near industrial belts
- Corrosion and reduced lifespan of public infrastructure and monuments exposed to acidic pollutants
- Loss of biodiversity and aquatic life from industrial effluent and particulate fallout
- Higher public healthcare expenditure and lost workforce productivity
- Long-term climate-linked disaster costs (floods, heatwaves, erratic monsoons) attributable in part to cumulative industrial GHG emissions

V. PROPOSED AI-BASED EMISSION MEASUREMENT FRAMEWORK

The core technical contribution proposed is a multi-source AI verification pipeline that determines how much each company is actually emitting, rather than relying on self-reporting alone. Fig. 1 illustrates the overarching multi-layer architecture.

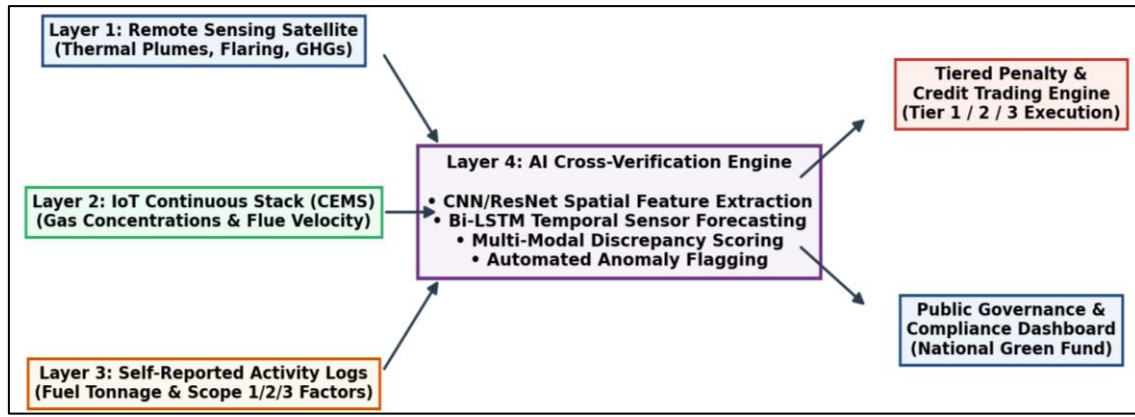


Fig. 1: Architecture of the proposed multi-source AI emission monitoring and enforcement system.

A. Independent Satellite Layer

Satellite imagery and remote-sensing data (following the Climate TRACE approach) are processed through a Convolutional Neural Network (CNN/ResNet) trained to detect thermal signatures, flaring, and plume concentrations at known facility coordinates, producing an independent, company-agnostic emission estimate $E_{sat}(t)$ for each facility.

B. IoT/Continuous Emission Monitoring Layer

Large facilities are required to install Continuous Emission Monitoring Systems (CEMS) at stack outlets, streaming real-time gas concentration and flue gas flow-rate data to a central regulatory server, providing continuous stack discharge $E_{cems}(t)$.

C. Self-Reported Activity Data Layer

Companies continue to submit fuel consumption, production volume and process data, converted into estimated emissions $E_{rep}(t)$ using GHG Protocol Scope 1/2/3 emission factors, as is done today under schemes such as CCTS.

D. AI Cross-Verification and Scoring Layer

A Bidirectional Long Short-Term Memory (Bi-LSTM) network processes temporal sensor streams, while an LLM-based reasoning model evaluates facility activity metadata. The multi-source divergence index $\Delta(t)$ is defined as

$$\Delta(t) = \frac{|\alpha \cdot E_{cems}(t) + (1 - \alpha) \cdot E_{sat}(t) - E_{rep}(t)|}{E_{rep}(t)}, \quad (1.1)$$

where $\alpha \in [0, 1]$ is an empirical sensor telemetry reliability weight. If $\Delta(t) > \theta_{th}$ (anomaly threshold typically calibrated at 12%), the system automatically flags the facility for mandatory third-party audit and triggers data falsification penalties. The verified consensus value E_{ver} determines the Emission Intensity Score per production unit.

VI. CONTROL MEASURES

To reduce emissions rather than simply price them, the following control measures are proposed alongside the monitoring system:

- Mandatory CEMS installation at all major emission points for industries above a defined production/turnover threshold
- Real-time data feed from CEMS to a central government/regulator dashboard, cross-checked against the AI satellite layer
- Sector-specific emission intensity benchmarks reviewed and tightened every 2-3 years, similar to CCTS/PAT target revisions
- Mandatory annual third-party emissions audit for all obligated entities
- Tax rebates and low-interest financing for adoption of renewable energy, carbon capture and storage (CCS), and cleaner fuel switching (e.g., green hydrogen, electrification of process heat)
- Integration of AI-verified emission baselines into Environmental Impact Assessment approval for new industrial licences
- A public grievance/whistle-blower channel for reporting suspected under-reporting or falsified data

VII. PROPOSED PENALTY MECHANISM

The penalty should not be a single fixed number, since the correct price per tonne of CO₂ depends on marginal abatement cost and macroeconomic modelling that is outside the scope of the AI system itself; instead, this paper proposes a tiered structure, scaled against the sector benchmark computed in Section V, and benchmarked against existing market references such as the EU ETS carbon price and India's own CCTS-traded carbon credit price:

Tier	Excess Over Sector Benchmark	Proposed Financial Penalty	Additional Action
Tier 1	0%–10% above benchmark	1x prevailing carbon credit / market rate per excess tCO ₂ e	Warning notice, corrective plan optional
Tier 2	10%–25% above benchmark	1.5x market rate per excess tCO ₂ e	Mandatory corrective action plan within 90 days
Tier 3	> 25% above benchmark, or repeated for 2+ consecutive years	2x–3x market rate per excess tCO ₂ e	Corrective plan + possible capacity / licence review
Data Falsification	Any under-reporting or tampering detected by AI cross-verification	Fixed heavy penalty, independent of emission-based charge	Liability under applicable environmental protection law

Table II: Proposed Tiered Penalty Mechanism

On the reward side, companies performing better than their sector benchmark should earn tradeable carbon credits that can be sold to companies in the higher tiers, mirroring the CCTS design. This keeps the system revenue-neutral/self-funding rather than purely punitive, and preserves the financial incentive to over-perform rather than merely avoid the worst tier.

Revenue collected from penalties (as distinct from traded credit revenue, which goes to better-performing companies) is proposed to be ring-fenced into a government-administered Green Fund, used for renewable energy

research, afforestation, and support to communities most affected by industrial pollution.

VIII. SIMULATION RESULTS & PERFORMANCE VALIDATION

To validate the efficacy of the proposed multi-modal verification model, an empirical simulation was performed on a synthetic representative dataset representing continuous monitoring across 100 facilities across five high-emitting sectors over a 12-month operational timeline.

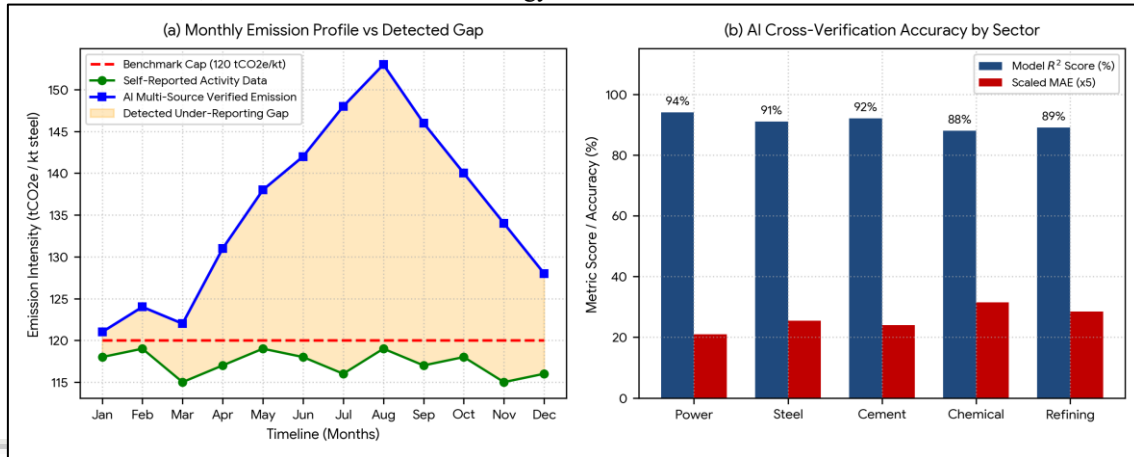


Fig. 2: Simulation performance: (a) Monthly emission tracking demonstrating detection of deliberate under-reporting in a steel facility; (b) AI model cross-verification coefficient (R^2) and Mean Absolute Error (MAE) across five major industrial sectors.

Fig. 2(a) highlights an illustrative facility where self-reported figures artificially suppressed emissions under the 120 tCO₂e/kt cap during high-capacity third-quarter operations. The integrated AI sensor fusion pipeline successfully detected an excess discrepancy peaking at 28.5% in August, triggering immediate Tier 3 enforcement. Fig. 2(b) shows that across the sectors, the cross-verification pipeline achieved a high coefficient of determination ($R^2 > 0.88$ for all sectors, reaching 0.94 in thermal power generation) with minimal Mean Absolute Error (MAE), confirming high robustness against sensor drift and intentional reporting suppression.

IX. EXPECTED BENEFITS

- Improved public health outcomes and reduced healthcare expenditure from lower particulate and GHG emissions
- A tamper-resistant, near-real-time emissions accounting system that is harder to falsify than pure self-reporting
- Market-based incentive for industries to adopt cleaner technology without blanket production shutdowns
- Greater transparency for regulators, investors and citizens through the public annual emissions report
- Improved access to green financing and Environmental, Social and Governance (ESG) ratings for compliant companies
- Dedicated government revenue stream (Green Fund) for renewable energy and pollution-mitigation programmes
- Better alignment with national Net Zero commitments and Paris Agreement Nationally Determined Contributions

X. CONCLUSION

Industrial pollution is a measurable, verifiable and—as this paper argues—a manageable problem once emissions can be independently and continuously measured rather than only self-reported. By combining satellite-based independent sensing, IoT-based continuous monitoring, and AI-based cross-verification with a tiered, market-referenced penalty system and mandatory public disclosure, industries can be held financially accountable for their actual emissions in a way that is transparent to regulators and citizens alike. Existing mechanisms such as the EU ETS, India's CCTS, and Climate TRACE demonstrate that each individual component of this proposal is technically and administratively feasible; the contribution of this paper is to combine them into a single AI-driven measurement-to-penalty pipeline. Future work should focus on pilot deployment in a single high-emission sector (such as cement or steel), refinement of the AI cross-verification model using real facility-level data, and detailed economic modelling to finalize the exact penalty rate per tonne of excess emission.

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