IoT platform for automated CO_2 measurement and direct quota calculation[*]

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Abstract

This article presents a proof-of-concept IoT platform for automated CO_2 emissions monitoring and direct carbon quota calculation at the software level. Instead of physical sensors, a Python-based digital twin was developed to generate synthetic ppm data incorporating sinusoidal oscillations, random noise, and linear drift. The raw values undergo two-point calibration (a = 1.02; b = −5) and are converted to tonnes per hour using the density of CO_2. To assess accuracy, an "ideal" noise- and drift-free sinusoid is generated and compared against the calibrated measurements. The primary purpose of this work is therefore not limited to channel emulation but to validate the feasibility of an end-to-end IoT pipeline covering the entire data lifecycle – from data generation and calibration to quota calculation and registry integration. While the present model is limited to CO_2 as a baseline indicator, it establishes a solid foundation for future extensions toward multi-component mixtures and adsorption dynamics. The results confirm the viability of the proposed "generation → processing → quota calculation → registry" architecture and provide a basis for integration with real IoT devices, MQTT/REST networking protocols, and the national emissions trading system.

Keywords

IoT; digital twin; CO_2 monitoring; calibration; emissions quotas; Python emulation; emissions trading system.

1. Introduction

In the era of pervasive digitalization, the Internet of Things (IoT) has emerged as a novel paradigm for monitoring carbon emissions. IoT can be defined as a network of interconnected physical devices, instruments, and other objects equipped with sensors and software, all linked via the Internet to collect, store, analyze, and exchange data and derived insights [1], [2], [3]. Market forecasts estimate that the global IoT market will reach USD 445.3 billion by 2025 and soar to over USD 934 billion by 2033 – more than tripling revenue within a decade – while the number of connected IoT devices worldwide is expected to triple over the same period [4].

Contemporary industrial CO_2 monitoring systems primarily rely on Continuous Emissions Monitoring Systems (CEMS), which cover roughly 70 % of carbon emissions in the power sector [5], as well as on comprehensive energy-management platforms such as Siemens' SIMATIC Energy Manager, Schneider Electric's EcoStruxure, Johnson Controls' Metasys, Honeywell Forge, and IBM Envizi [6]. A key component of the European Emissions Trading System (ETS) is its quota-allocation mechanism, and accurate enterprise-level CO_2 monitoring underpins effective ETS operation and transparent carbon-quota trading. Although these systems deliver high measurement fidelity and data collection, their integration with reporting tools (e.g., the EU ETS Reporting Tool) often requires manual data uploads and does not guarantee real-time quota adjustment. Digital solutions such as Predictive Emissions Monitoring Systems (PEMS) use historical data to estimate emissions but do not support fully automated quota calculation and registration, leading to decision-making delays and

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increased risk of inaccuracies. N. Ding et al. (2025) emphasize that achieving high accuracy in low-concentration CO_2 measurements critically depends on robust calibration and quality-control mechanisms [5]. Moreover, traditional monitoring methods exhibit limitations – low accuracy and sampling frequency, significant hysteresis, and limited reliability [7]. Ding et al. further highlight that comprehensive carbon accounting, which is most widespread, demands precise recording of carbon-footprint activities, a requirement that often exceeds the financial capacity of small and medium-sized enterprises and is further undermined by human error [5].

Ukraine is currently preparing to implement a national emissions-trading system, as mandated by its Association Agreement with the European Union. This initiative imposes stringent requirements on the transparency, timeliness, and reliability of greenhouse-gas reporting. The absence of an integrated "sensor-to-registry" data transfer mechanism creates a potential gap between on-site quota calculations and their official verification in the state registry. In response, this work develops and tests a proof-of-concept IoT platform featuring a Python-based digital twin of the sensor to generate synthetic CO_2 data, apply two-point calibration, and automatically compute quota volumes for submission to an experimental "mock" registry. The proposed "sensor ⟶ quota-calculation ⟶ registry" architecture demonstrates the technical feasibility of an end-to-end integration model and provides a foundation for future deployment with physical IoT devices, MQTT/REST protocols, and national reporting systems in the context of Ukraine's emissions-trading system.

The primary purpose of this study is therefore not limited to channel emulation, but to validate a proof-of-concept IoT pipeline covering the entire data lifecycle – from digital-twin based data generation through calibration and quota calculation to registry integration.

2. Literature review

For effective emissions monitoring, intelligent management via the Internet of Things has been investigated across various sectors – primarily energy, manufacturing, and construction [5]. According to the International Energy Agency, carbon emissions from the energy sector in 2022 accounted for approximately 40 % of global emissions, making it the largest industrial source of carbon output and energy consumption [8].

A. Arsiwala, F. Elghaish, and M. Zoner (2023) explored pathways to carbon neutrality by proposing an integrated IoT and AI solution – key components of a digital twin – implemented as an interactive monitoring dashboard [9]. S. Winter et al. (2025) introduced a unified digital-twin framework and data model that enable seamless, continuous information exchange among all stakeholders [10].

Y. Jiang and Z. Mao (2025) note that carbon-emissions monitoring is critical for implementing reduction strategies, yet excessive reliance on detailed energy data and manual calculations renders the data-collection process low-frequency, time-lagged, and unreliable. They proposed an ICEEMDAN-Inception-Transformer model capable of providing accurate hourly carbon-emissions data collection for energy-sector enterprises [11].

Li Qingqing et al. (2024) argue that achieving carbon neutrality requires an efficient, reliable carbon ecosystem comprising regulatory bodies, emissions-reduction organizations, and independent auditors. They developed the Modelx+MRV+O system based on IoT and blockchain technologies [12]. Blockchain and IoT can ensure data integrity, transparency, and immutability, facilitating the dissemination of carbon credits within the toolkit of emissions-reduction measures [13], [14].

3. Methodology

In our work, we have implemented a software pipeline in pure Python that emulates the complete CO_2 emissions monitoring data lifecycle – "generation ⟶ processing ⟶ storage ⟶ analysis" (Figure 1). In the first stage, the sensor emulator module produces a sequence of ppm readings by modeling ambient concentration as a sinusoidal waveform, overlaid with random Gaussian noise and a linear drift from the initial timestamp. Each data point is tagged with its send time and enqueued into a Python internal queue, which acts as the sole communication channel between the generator and the processor.

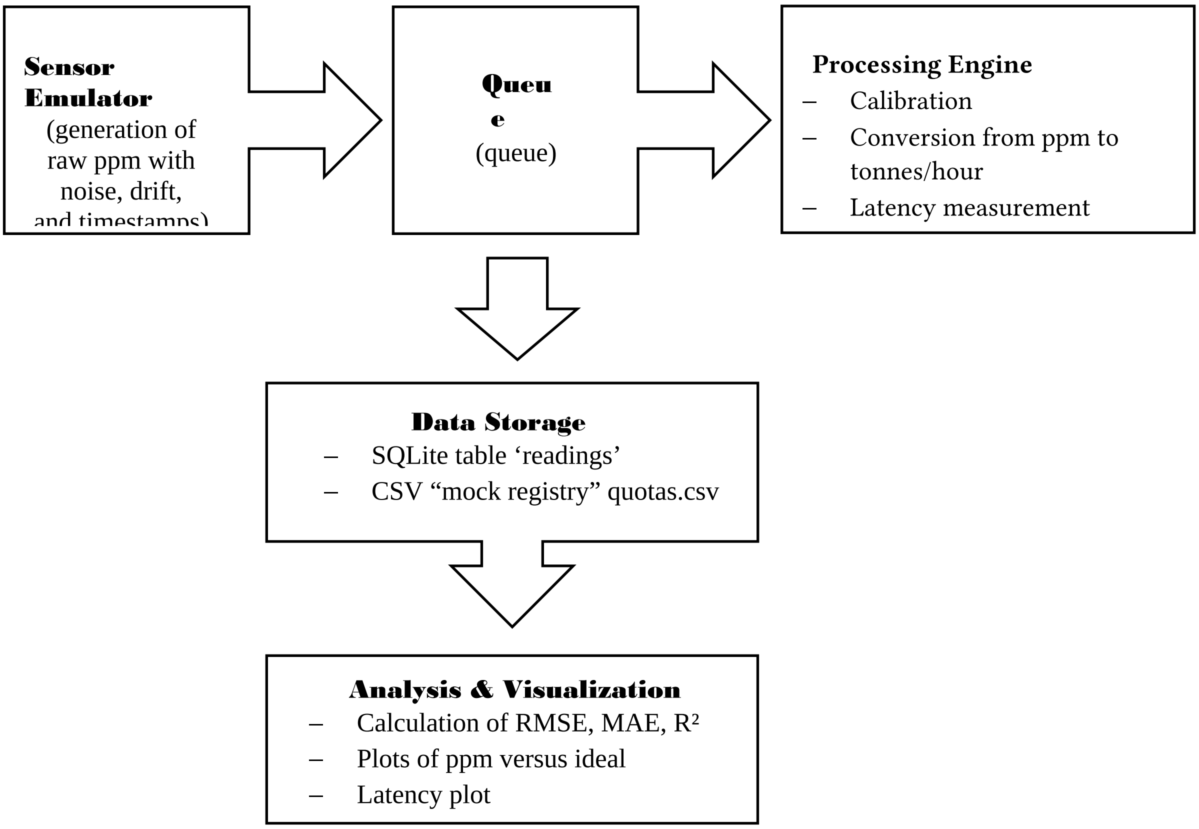

Figure 1: Block diagram of the “generation → processing → storage → analysis” pipeline for the IoT platform for automated CO_2 monitoring and quota calculation.

The sensor emulator generates a series of NUM_SAMPLES (100) observations at a fixed interval (0.5 s). One hundred measurements provide a statistically significant dataset for metric evaluation, and the 0.5 s interval allows the full dataset to be collected in 50 s while maintaining sufficient resolution to capture the waveform and noise.

For each measurement, the following are computed:

1. The base sinusoid modeling the cyclic variation in concentration is given by:

$$base = 400 + 200 \cdot \left(\frac{\sin\left(t - t_0\right)}{600} + 1 \right), \tag{1}$$

where t_0 is the start time of the series.

This value corresponds to ideal_ppm, i.e., ideal_ppm=base. The parameters were selected with the following considerations:

400 ppm – the approximate mean background CO_2 concentration in the atmosphere at ground level.

±200 ppm – the amplitude of cyclic fluctuations, yielding a wave from 200 to 600 ppm; this simulates daily concentration changes resulting, for example, from variations in industrial activity or diurnal photosynthetic uptake by vegetation. This wider span was intentionally chosen to test the robustness of calibration and to approximate possible variations observed in localized industrial or environmental settings.

600 s in the denominator of the sine argument sets the oscillation period to about 10 minutes in the “accelerated” timescale, allowing many daily-like cycles to be emulated within a short measurement session.

2. Random noise, modeled as

$$noise \sim N(0{,}10)\,ppm. \tag{2}$$

A standard deviation of 10 ppm represents a typical level of fluctuation observed in consumer or semi-industrial NDIR sensors over a single measurement session. This magnitude of noise introduces sufficient variability without distorting the overall waveform.

3. Linear drift, defined as

$$drift = \frac{t - t_0}{86400} \cdot 0.1\,ppm/day. \tag{3}$$

0.1 ppm/day – a small, slow drift typical of NDIR modules caused by temperature variations or sensor aging. It is divided by 86400 s (24 h) so that each second contributes only a minute offset. In the accelerated simulation timescale used in our experiment, this drift is proportionally added to each generated data point, ensuring that long-term sensor instability is represented even within short measurement sessions.

As a result, we obtain the final raw ppm value $ppm_{raw} = base + noise + drift$ together with the send timestamp t_{send} and the elapsed time from the start, $res_{ts} = t - t_0$.

In the collector, each “message” is read from the queue, the receive time t_{recv} is recorded, and the latency is computed as $latency = t_{recv} - t_{send}$. Calibration is performed using a two-point method:

$$ppm_{corr} = a \cdot ppm_{raw} + b, \tag{4}$$

where $a = 1.02$, $b = -5$.

These coefficients were chosen to align two anchor points: when the raw sensor reads 400 ppm, the correction brings it close to the true 400 ppm, and when it reads 1000 ppm, it brings it close to 1000 ppm. A linear regression through these two reference points provides a quick adjustment of the sensor’s output to a calibrated instrument. This simple linear correction compensates for the sensor’s systematic bias.

The corrected ppm values are converted to tonnes per hour using the classical formula:

$$\rho_{CO_2} = 1.977\ \frac{kg}{m^3}, \tag{5}$$

$$m_{kg/s} = \frac{ppm_{corr}}{10^6} \cdot \rho_{CO_2}, \tag{6}$$

$$M_{t/h} = m_{kg/s} \cdot \frac{3600}{1000}. \tag{7}$$

The density of CO_2 $\left(1.977\ \frac{kg}{m^3}\right)$ is the physical value under standard conditions (1 atm, 25 °C). It is used to convert concentration (ppm) into a mass flow rate (kg/s). We then apply a factor of 3600/1000 to convert kg/s into tonnes/hour. This step simulates the transformation of concentration into a mass emission rate.

Simultaneously, all processing results are written to a local SQLite database (the readings table for raw and calibrated ppm values and mass flow) for persistent storage and to a CSV file (quotas.csv) acting as a “mock registry” of quotas, thereby simulating integration with the national emissions trading system.

In the final step, the analytics module selectively reads the accumulated data, generates an “ideal” noise- and drift-free sinusoidal curve, and compares it with the calibrated data stream by computing the root mean square error (RMSE), mean absolute error (MAE), and the coefficient of determination (R^2).

$$RMSE_{ppm} = \sqrt{\frac{1}{N} \cdot \sum_{i=1}^{N} \left(ppm_{corr_i} - ideal_{ppmi} \right)^2}, \tag{8}$$

$$MAE\_ppm = \frac{1}{N} \sum_{i=1}^{N} \left| ppm_{corr_i} - ideal\_ppm_i \right| \tag{9}$$

$$R^2\_ppm = 1 - \frac{\sum_{i=1}^{N} \left(ppm_{corr_i} - ideal\_ppm_i \right)^2}{\sum_{i=1}^{N} \left(ideal\_ppm_i - \overline{ideal\_ppm} \right)^2}, \quad \overline{ideal\_ppm} = \frac{1}{N} \sum_{i=1}^{N} ideal\_ppm_i \tag{10}$$

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These metrics enable the assessment of how closely the synthetic data stream matches the “ideal” by using our noise- and drift-free model based on the same underlying sinusoid but without any random components.

At each step, performance (latency) was measured as the difference between the send timestamp and the in-memory processing time. Concurrently, a latency distribution plot for each message was generated. The number of sent versus received messages (packet-loss) was also calculated.

Thus, the methodology encompasses the entire data lifecycle: parameterized data generation, calibration, quota calculation, validation, and pipeline performance evaluation. This provides a solid foundation for subsequent integration with real IoT devices and the national emissions trading system.

4. Results

For quantitative evaluation of the accuracy and performance of the developed data pipeline, a series of identical test runs were conducted in a controlled environment. The obtained results enable a direct comparison of the system’s behavior with the theoretical model, free from external latency factors.

These controlled experiments made it possible to evaluate both the accuracy of the synthetic sensor emulation and the stability of the processing pipeline. In particular, we examined how closely the calibrated data follow the ideal sinusoidal pattern and quantified the impact of noise and drift on the overall measurement quality. This setup also allowed us to assess the end-to-end performance of the pipeline in terms of latency, packet loss, and statistical error metrics.

In a 50-second session with a 0.5 s interval, 100 messages were generated and processed. To compare the calibrated measurements against the reference noise- and drift-free sinusoid, Figures 2–3 present the plot of ppm_{corr} versus ideal_ppm and the calculated versus ideal CO_2 emissions in tonnes per hour.

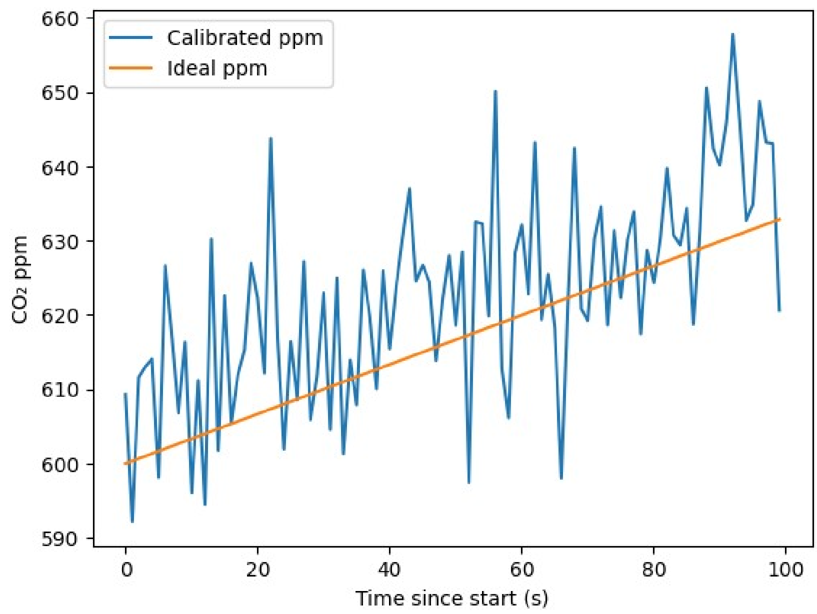

Figure 2: Comparative Plot of Calibrated Versus Ideal CO_2 Concentration Values.

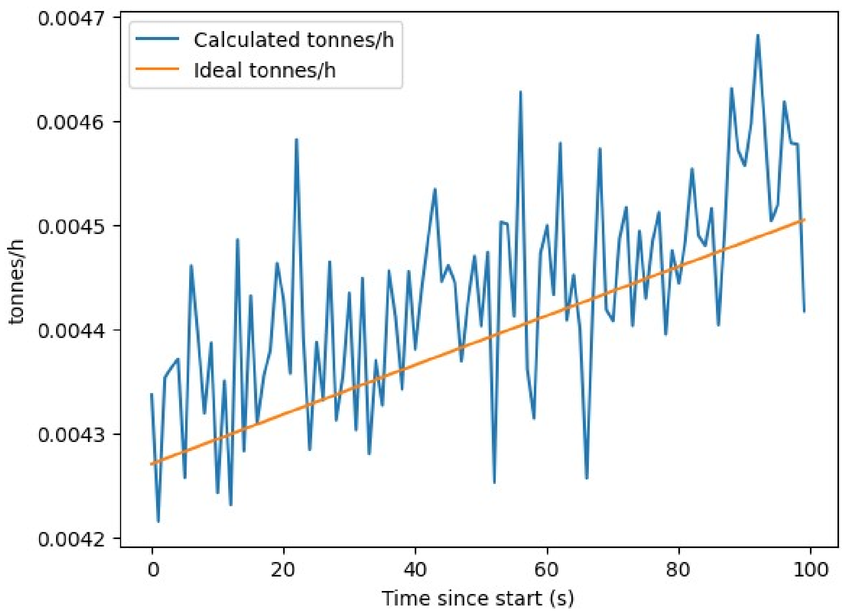

Figure 3: Comparative Plot of Calculated Versus Ideal CO_2 Emissions in Tonnes per Hour.

These figures clearly illustrate how random noise and drift scatter the real data around the ideal curve, underscoring the need for further smoothing and adaptive calibration to reduce these discrepancies.

To remove high-frequency noise, we applied a simple 5-point moving average (Figure 4). After smoothing, the RMSE decreased from 11.85 to 8.82 ppm.

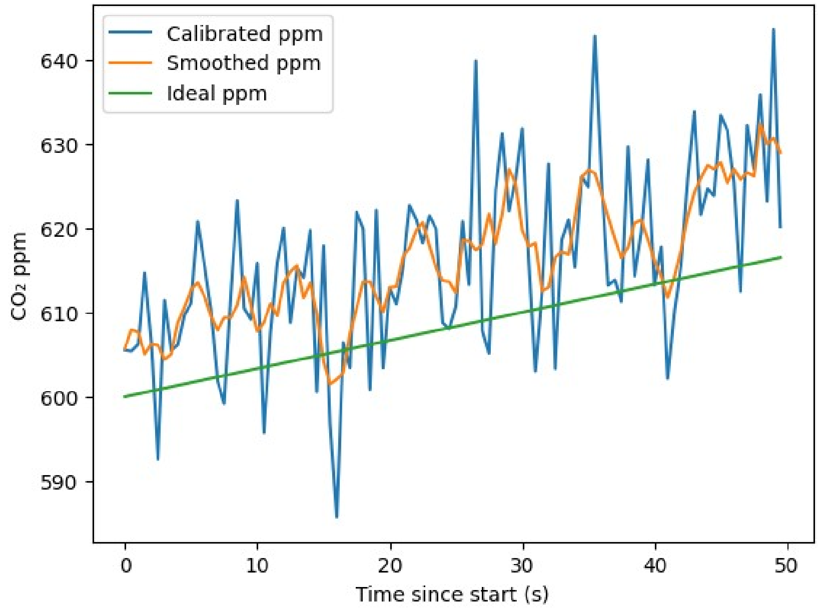

Figure 4: Comparative Plot of Calibrated Data, 5-Point Moving Average Results, and Ideal Sinusoid in ppm.

As shown in Figure 4, the moving average effectively smooths out high-frequency noise fluctuations, bringing the measured curve closer to the underlying trend while preserving the overall rising shape of the concentration. This confirms the appropriateness of applying filtering to enhance the stability and accuracy of the monitoring algorithm.

The values of the key performance indicators resulting from the simulation are presented in Table 1.

Table 1
Key Accuracy and Performance Indicators of the Digital CO_2 Monitoring Pipeline

Indicator	Value	Description
RMSE_ppm	8.82 ppm	Root mean square error between calibrated ppm and ideal sinusoidal values
MAE_ppm	7.65 ppm	Mean absolute error; on average measurements deviate by 7–8 ppm
Mean Error_ppm	0.73 ppm	Mean bias error, indicating a slight systematic offset
Median Error_ppm	1.2 ppm	Median of the error distribution; half of the measurements lie within ±1.2 ppm
Std Dev Error_ppm	11.1 ppm	Standard deviation of errors, indicating the spread of the error distribution
Min Error_ppm	−25.4 ppm	Maximum underestimation during the session
Max Error_ppm	+29.8 ppm	Maximum overestimation during the session
R^2_ppm	0.286	Proportion of the ideal signal's variance explained by the calibrated data

RMSE_tonnes/h	0.0009 t/h	RMSE in tonnes per hour; approximately equivalent to ~9 ppm at the given flow rate
Latency_avg	0.000 s	Average in-memory processing latency per message
Latency_min / Latency_max	0.000 s / 0.000 s	Minimum and maximum latency, limited by Python's timer resolution
Packet loss	0.0 % (100/100)	No messages lost; all 100 messages processed successfully

This table demonstrates that both the modeling accuracy (RMSE, MAE, R^2) and the pipeline performance (latency and transmission reliability) remain within the bounds of a software-only emulation. The error distribution (ppm_{corr} − ideal_ppm) exhibits a mean bias of approximately 0.7 ppm, a median of 1.2 ppm, a standard deviation of 11.1 ppm, a minimum of −25.4 ppm, and a maximum of +29.8 ppm. All 100 messages were processed without any loss (packet loss = 0%) and with effectively zero latency (avg/min/max latency ≈ 0.000 s), underscoring the instantaneous in-memory processing of the Python script.

Figure 5 shows the distribution of processing latency for each of the 100 messages.

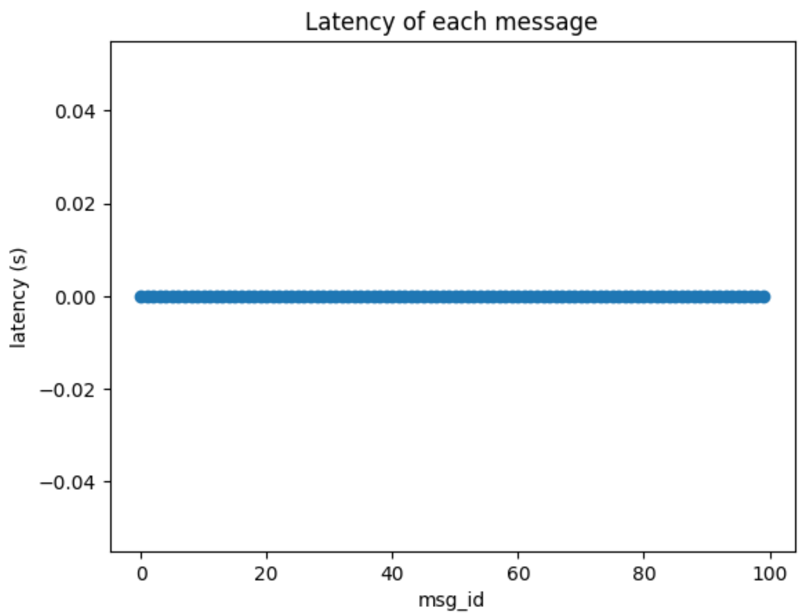

Figure 5: Distribution of Processing Latency for Each Message.

As shown in Figure 5, all points lie on the zero line (within the resolution of Python's timers), further confirming truly instantaneous in-memory processing without any real delays.

These results demonstrate an acceptable level of accuracy for the POC pipeline and its readiness for subsequent deployment with real networking protocols and sensors.

5. Discusion

The results make it clear that our software-only emulation of the end-to-end pipeline – from sensor to quota calculation – achieves the desired measurement accuracy and instantaneous data processing, while also highlighting several key areas for future work.

Although the sinusoidal model with added Gaussian noise and linear drift effectively mimics the basic behavior of NDIR sensors, actual devices are subjected to a far broader range of environmental and operational disturbances – temperature swings, humidity, particulate contamination, and electromagnetic interference. In real-world deployments, it will therefore be necessary to implement multi-point calibration or adaptive filtering techniques to correct accumulating errors.

The zero latency observed in our in-memory prototype demonstrates that pure software processing introduces no appreciable delay, but integrating a network layer (whether MQTT or REST) will inevitably add transit delays that depend on link quality and broker load. Industrial practice generally tolerates latencies of 1–2 seconds, so the next step should be to construct a testbed with emulated brokers and measure how these metrics evolve when the system scales to several dozen devices.

Integration with Ukraine's national emissions trading system (ETS) will require not only a robust data channel but also end-to-end message authentication, encryption, and auditability. A simple API key may be insufficient; public-key infrastructure (PKI) or even a distributed ledger (blockchain) could be considered to guarantee data immutability and trust.

Finally, the economic feasibility of such an automated pipeline must be assessed by weighing the deployment costs of sensors and supporting infrastructure against the time savings and error reductions in reporting. For small and medium-sized enterprises, bundling the core "software + digital twin" solution with outsourced calibration and maintenance services may lower the barrier to adoption.

It should be emphasized that the present proof-of-concept model is intentionally limited to CO_2 as a baseline indicator to validate the feasibility of an end-to-end IoT pipeline for automated quota calculation. In real industrial and environmental conditions, emission streams typically contain multi-component mixtures such as CO_2, CH_4, NO_x (primarily NO and NO_2), and volatile hydrocarbons, and are subject to competitive adsorption, diffusion, and multiphase equilibrium processes. These phenomena significantly influence both the composition and the effective concentration of emissions. Future research should therefore extend the proposed platform by integrating multi-component models and adsorption dynamics, as highlighted in recent studies on CO_2/CH_4 interactions [15], adsorption modeling on activated carbon [16], and advances in CO_2 capture by absorption and adsorption [17]. Incorporating these aspects will considerably broaden the applicability of the IoT-based monitoring pipeline and make it more representative of real-world scenarios.

In summary, these preliminary findings validate the concept and raise several practical questions – how to adapt the algorithm to real sensors, how to secure a reliable transmission channel and comply with regulatory requirements, and how to develop a cost-effective service model under Ukraine's ETS. This work thus provides a springboard for subsequent field trials, large-scale deployments, and full integration with physical IoT hardware and national registry systems.

6. Conclusion

The experimental results validate the effectiveness of the proposed "sensor ⟶ processing ⟶ storage ⟶ analysis" pipeline implemented entirely in software. By employing a Python-based digital twin that generates a sinusoidal baseline overlaid with Gaussian noise and a slow linear drift, we achieved a root-mean-square error (RMSE) of approximately 9 ppm and a coefficient of determination (R^2) of about 0.29 following two-point calibration. The complete absence of message loss and the near-zero in-memory processing latency demonstrate the extraordinary speed and reliability of the internal data pipeline.

This proof-of-concept platform lays a solid foundation for further practical and experimental work – especially in light of Ukraine's forthcoming national emissions trading system (ETS), which demands stringent data timeliness and accuracy. The architecture supports field trials with actual NDIR sensors, encompassing temperature- and humidity-dependent errors and multi-point calibration schemes. Future development will extend the pipeline to real-world deployments by integrating MQTT/REST protocols (introducing realistic network latencies and risks), porting computational modules to microcontrollers, and establishing a secure transmission channel with authentication and encryption for direct ETS registry uploads. Careful economic modeling of platform maintenance and calibration services for small and medium-sized enterprises will be essential to ensure accessibility and cost-effectiveness under resource constraints. In sum, the proposed software pipeline represents a crucial stepping stone toward a full-scale IoT platform for automated CO_2 monitoring and direct quota calculation within state registries.

At the same time, we acknowledge that the present proof-of-concept is limited to CO_2 as a single-component indicator. In real industrial conditions, emission streams contain multi-component mixtures and are affected by competitive adsorption and multiphase equilibrium. Addressing these phenomena in future versions of the platform will further increase its applicability and bring the IoT-based pipeline closer to real-world deployment.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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