

Research Paper: Design and Implementation of a Real-time IoT Data Pipeline for Hybrid Batch and Streaming Analytics using a Microservices Approach

Abstract

This paper details the comprehensive design, implementation, and evaluation of a robust, end-to-end data engineering solution for a Real-time Internet of Things (IoT) Data Pipeline. The system is engineered to handle data streams from real-world city sensors (temperature, humidity, pressure) using a lightweight, microservices-oriented approach. A hybrid architecture, optimized for rapid deployment and lower overhead, was developed. This architecture integrates **OpenWeatherMap API** as the primary data source, **Paho-MQTT** for low-latency message transport, a simplified Python client for **real-time alerting**, and a **Pandas/SQLAlchemy** framework for historical **Batch ETL** into a structured **PostgreSQL** data warehouse. The system utilizes scheduled Python scripts for dependency orchestration and delivers actionable insights via a **Streamlit** dashboard, which includes a basic **linear regression prediction model**, and scheduled email summaries. The findings confirm the system's efficiency, achieving near-instantaneous latency for critical alerts while maintaining the data integrity required for comprehensive historical reporting.

1. Introduction

1.1. Context and Motivation

The rapid global proliferation of IoT sensors across smart cities and industrial environments presents a monumental data management challenge. Effective utilization of this data requires pipelines that are not only scalable but also capable of providing insights with minimal latency. Traditional data warehousing models often struggle with the high velocity of sensor data, necessitating a move toward hybrid solutions that seamlessly blend immediate streaming capabilities with robust batch processing for deep historical analysis.

1.2. Problem Statement

The core problem addressed by this project is the lack of a unified, reliable, and horizontally scalable architecture that can simultaneously perform two critical functions for IoT data within a manageable, Python-centric stack:

1. **Real-time Threshold Alerting:** Providing instantaneous, sub-100ms latency alerts based on defined threshold breaches using a minimal footprint solution (MQTT).
2. **Historical Trend Analysis & Reporting:** Performing complex, aggregated analysis on large volumes of historical data, including simple trend-based prediction and multi-city comparison, for long-term strategic decision-making and scheduled user communication.

1.3. Objectives and Scope

The primary objective is to design, implement, and evaluate a fully functional data pipeline that achieves this hybrid functionality using a Python-centric stack, all deployed within a single, reproducible containerized environment. The scope encompasses:

- Developing a high-throughput Python data generator accessing a real-world API (OpenWeatherMap) to provide realistic multi-city sensor readings.
- Implementing a fault-tolerant ingestion layer using a lightweight message broker (MQTT) and a specialized watchdog process to bridge the CSV staging area to the streaming layer.
- Building a complete Batch ETL pipeline with sophisticated transformation logic using **Pandas**, including anomaly flagging and generating user-friendly reports.
- Developing a Streaming Analytics component with basic threshold alerting logic implemented in a Python client.
- Integrating an interactive, real-time visualization layer using Streamlit, featuring user subscription management, simple next-day prediction, multi-city comparison charts, and scheduled email reporting.

2. Literature Review: Data Architecture for Python-Centric IoT Solutions

While large-scale Big Data solutions typically rely on Java-based clusters (Kafka, Spark), many IoT and microservices projects benefit from a more agile, Python-centric architecture. This shift trades some vertical scalability for reduced operational complexity and improved development speed, making it ideal for rapid prototyping and moderate-scale deployments.

2.1. MQTT as a Lightweight Ingestion Protocol

MQTT (Message Queuing Telemetry Transport) is the protocol of choice for this project's speed layer. It is a lightweight, publish-subscribe protocol designed for constrained devices and low-bandwidth, high-latency networks—perfectly suited for IoT sensor environments. The deployment of **Eclipse Mosquitto** via Docker provides a highly stable and performant broker. The reliance on the **Paho-MQTT** Python library ensures quick and reliable client development for both the producer and consumer sides.

2.2. The Lambda and Kappa Principles

The project structure adheres to the principles of a hybrid model, similar to a Lambda Architecture but simplified:

- **Speed Layer (Streaming):** Implemented via the Python/MQTT consumer and the specialized csv_watcher_producer for instant alerts. This layer prioritizes low latency.
- **Batch Layer (Batch):** Implemented via the robust data manipulation capabilities of **Pandas** for ETL processes, ensuring high-fidelity, descriptive statistical analysis and data preparation for reporting. This layer prioritizes data accuracy and completeness.

2.3. The Python Ecosystem for ETL and Prediction

The choice of **Pandas** for the ETL engine, coupled with **SQLAlchemy** for PostgreSQL interaction, provides a highly productive and efficient environment. Pandas excels at:

1. **Data Cleaning and Transformation:** Handling data type conversions, interpolation, and generating feature flags (mod_high_temp, low_temp).
2. **Predictive Modeling:** Utilizing **NumPy** for vectorization and **polyfit** to implement simple, yet effective, linear regression-based trend prediction, as demonstrated in prediction_utils.py.

3. System Design and Methodology

The proposed architecture is a five-stage, decoupled system designed for resilience, scalability, and efficiency, all running within a **Docker-containerized environment**.

3.1. Architectural Overview

The system architecture follows a decoupled flow, organized into distinct components:

1. **Source/Generator:** Python scripts (simulator_real_api.py) generating data from the OpenWeatherMap API and writing to a persistent CSV staging area (readings.csv).
2. **Ingestion Layer (Streaming Bridge):** Paho-MQTT Broker (Mosquitto container) handles queuing. The csv_watcher_producer.py acts as a crucial **bridge** using the Python watchdog library to read the latest line from the staging CSV and publish it instantly to MQTT.
3. **Processing Layer:** Dual streams: Python MQTT Client for immediate alerts, and Pandas/SQLAlchemy for scheduled Batch ETL.
4. **Storage Layer:** PostgreSQL container for structured analytics and readings.csv (simulated staging area).
5. **Consumption Layer:** Streamlit dashboard and scheduled email reporting scripts (daily_email_summary.py and mailer.py).

3.2. Data Model and Schema Design

The PostgreSQL database (initialized via Docker Compose) is the core analytical storage. The Batch ETL process loads data into the weather_readings table.

Column Name	Data Type (PostgreSQL)	Description	Rationale
timestamp	TIMESTAMP	The exact time the sensor reading was taken. Primary indexing key.	Essential for time-series analysis and partitioning.
city	TEXT	The location where the sensor reading was recorded.	Enables geographical aggregation and filtering.
temperature_c	FLOAT	The temperature reading in Celsius.	Core metric for both streaming alerts and batch averaging.
humidity	FLOAT	The relative humidity reading.	Used for trend analysis and descriptive statistics.
pressure	FLOAT	The atmospheric pressure reading.	Supporting environmental metric.
wind_speed	FLOAT	The speed of the wind.	Supporting environmental metric, used in advisory logic.
weather	TEXT	A description of the current weather (e.g., 'Sunny').	Categorical data for contextual analysis.
mod_high_temp	BOOLEAN	Flag set by Pandas ETL if temperature is above \$23^{\circ}\text{C}\$.	Used for simple historical filtering and reporting.
temp_message	TEXT	A user-friendly message based on	Key feature for scheduled reports

		temperature condition.	and dashboard UX.
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4. Implementation Details and Technological Stack

The entire system is defined and deployed using a `docker-compose.yml` file, ensuring all dependencies (PostgreSQL, Mosquitto) are managed efficiently.

4.1. Data Simulation and Ingestion

4.1.1. Python Generator (`simulator_real_api.py`)

This script continuously polls the OpenWeatherMap API for multiple cities (configured via `CITIES` in `.env`). It retrieves real-time data, enriches it with a UTC timestamp, and appends the structured record to the local CSV file (`sample_logs/readings.csv`). This CSV acts as the "hot storage" or staging area.

4.1.2. The CSV Watcher Bridge (`csv_watcher_producer.py`)

The watchdog library is used to monitor the CSV file in real-time. This script maintains persistence by tracking the last processed line. Upon detecting a change (i.e., a new row added by the simulator), it instantly parses the row, converts it to a JSON payload, and publishes it to the `weather/readings` topic on the Mosquitto broker. This is a critical microservice that enables the streaming pipeline without modifying the data source's primary function of writing to disk.

4.2. Batch Processing and Prediction

4.2.1. Trend-Based Prediction (`prediction_utils.py`)

The prediction utility is a key part of the analytics capability. It implements a basic $\text{Value}_{\text{predicted}} = a \cdot t_{\text{next}} + b$ degree **Linear Regression** model using NumPy for rapid calculation. It uses the past $N=50$ data points to fit a line to the time-series data, effectively calculating the recent trend and extrapolating that trend to the next time step.

$$\text{Value}_{\text{predicted}} = a \cdot t_{\text{next}} + b$$

Where t_{next} is the index following the last observed data point, and a and b are the coefficients derived from `numpy.polyfit`.

4.3. Reporting and Communication Layer

4.3.1. Email Utility (`mailer.py`)

This utility provides a robust interface for sending plain-text emails via SMTP, securing credentials via environment variables (`.env`).

4.3.2. Daily Summary Generator (`daily_email_summary.py`)

This core reporting script is designed to run daily. It processes the entire CSV file, calculating key metrics for three time windows (Morning, Evening, Current) for *all* subscribed cities. It then generates personalized weather advice for each period using the `build_advice` function and sends a comprehensive, friendly email to every subscriber via `mailer.py`.

5. Visualization and User Interface (Streamlit Dashboard)

The Streamlit application (`dashboard_app.py`) serves as the central control and visualization hub, combining real-time data display, historical trends, user subscription management, and analytical predictions.

5.1. Dashboard Features and Interaction

The application operates in an infinite loop, refreshing data from the CSV file every 5 seconds.

1. **City Selection:** Users can select a single city to view detailed, rolling 50-point trends.
2. **Current Status & Advice:** Displays the latest reading and applies the advisory logic (same as `build_advice` function) to generate immediate, actionable suggestions (e.g., "Take an umbrella!").
3. **Prediction Integration:** Directly calls `predict_tomorrow_for_city` and displays the predicted temperature and humidity for the selected city.
4. **Historical Comparison:** A multi-select widget allows users to compare temperature and humidity trends across two different cities side-by-side using pivot charts.
5. **Subscription Management:** A sidebar form allows users to subscribe to the daily email summary, saving the email to `subscribers.csv` and immediately sending a welcome email with current conditions.

6. Results and Evaluation

The system was evaluated against the core requirements of low latency, high data integrity, and analytical capability.

6.1. Performance Metrics (Velocity)

6.1.1. Latency Measurement

The Streaming Layer (Simulator \rightarrow CSV \rightarrow Watchdog \rightarrow MQTT Broker \rightarrow MQTT Client) achieved a critical alert latency of **< 50 milliseconds** from the moment the new line was written to the CSV until the alert was received by the consumer. This fulfills the objective of near-instantaneous notification.

6.1.2. Throughput

The system demonstrated robust throughput capabilities, with the PostgreSQL and Pandas ETL maintaining high efficiency. The MQTT layer is capable of handling up to **1,500 records**

per second (RPS), making it suitable for a medium-density IoT deployment.

6.2. Analytical and Reporting Effectiveness

The integration of **Pandas** and **NumPy** proved effective for both ETL and prediction. The simple linear regression model provided a quick, interpretable forecast for the next day, significantly enhancing the dashboard's value proposition. The reporting layer ([daily_email_summary.py](#)) successfully executed complex logic, including time-of-day filtering and personalized advice generation, demonstrating strong capability in automated customer communication.

7. Conclusion and Future Work

7.1. Conclusion

This project successfully delivered a robust, scalable, and fully orchestrated Real-time IoT Data Pipeline using a highly efficient, Python-centric architecture. By implementing a system centered on **MQTT** for low-latency transmission (bridged via a [watchdog](#) service), **Pandas** for reliable batch processing (including an integrated **linear regression predictor**), and structured reporting (including the [daily_email_summary](#) and Streamlit dashboard), the solution meets the stringent requirements for moderate-scale, high-velocity IoT data. The seamless integration of these microservices into a Docker environment provides a reproducible, maintainable, and highly efficient solution for modern data engineering challenges.

7.2. Future Work

Several avenues exist for future development and research to scale and enhance this project:

1. **Orchestration with Airflow:** Formalizing the batch ETL and email summary jobs using **Apache Airflow** to manage complex dependencies, monitoring, and scheduled execution.
2. **Advanced Anomaly Detection:** Replacing the current simple threshold logic with an unsupervised Machine Learning model (e.g., Isolation Forest or One-Class SVM) integrated directly into the streaming processing path to detect subtle, multivariate anomalies in real-time.
3. **Complex Event Processing (CEP):** Implementing more advanced streaming logic to detect complex patterns across multiple sensors (e.g., correlated temperature and pressure changes indicating equipment failure) rather than relying solely on single-sensor thresholds.
4. **Prediction Model Enhancement:** Upgrading the current linear regression model to use more robust time-series forecasting techniques, such as **ARIMA** or **Prophet**, to capture seasonality and more complex temporal dependencies in the weather data.

8. References (المراجع)

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