Technology Arts Sciences TH Köln

Semester Assignment: Modern Database Systems Research Project

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Abbreviations

Abbreviation	Meaning
IoT	Internet of Things
UI	User Interface
CSV	Comma-Separated Values
SQL	Structured Query Language
NoSQL	Not Only SQL (non-relational database model)
ms	Milliseconds
ID	Identifier

Abstract

This paper compares the performance of two database systems InfluxDB 2.7 and Oracle Database 23ai Free for storing and querying large volumes of IoT telemetry data. The same dataset, which includes temperature, humidity, gas, and motion readings from sensor devices, was imported into both systems. Several typical time-series queries were executed, such as calculating average humidity per device, detecting maximum temperature, and estimating air quality based on gas values.

We implemented quantitative methods to investigate time performance for data extraction for each database. The results show that Oracle was generally faster for most queries, while InfluxDB offered better support for native time-series operations. These findings highlight important trade-offs when selecting a database system for time-centric IoT applications. The code base of this project can be find in the following GitHub Repository.

Project Repository: github.com/florivz/mds-influxdb

1 Introduction

InfluxDB is a time-series database designed for high performance and scalability. It uses a schema-less model that lets users add new fields without modifying existing schemas. InfluxDB supports specialized query languages such as InfluxQL and Flux, and also standard SQL. It can ingest large volumes of metrics and IoT data at high speed and is commonly used for monitoring, alerting, and real-time analytics[1]. Therefore, we decided to take a closer look at this open source project to investigate the real-world performance compared to a state-of-the-art SQL Database from one of the leading companies in that field.

2 Data Overview

The experiments in this project are based on the Environmental Sensor Telemetry Data set by Gary A. Stafford, published on Kaggle¹. The dataset file iot_telemetry_data.csv is approximately 61.9 MB in size and contains around 405,000 sensor readings. These readings were collected between 12 July 2017 and 19 July 2017 from three Raspberry Pi devices, each deployed in a different environment. The devices recorded various environmental variables and streamed the data to AWS IoT Core.

Data Preparation and Cleaning

Before loading the data into the databases, several transformations were performed in the respective initialization notebooks:

¹https://www.kaggle.com/datasets/garystafford/environmental-sensor-data-132k

Field	Description	Unit / Type
ts	Timestamp	seconds
device	Device ID (device_1-device_3)	string
temp	Temperature	$^{\circ}\mathrm{F}$
humidity	Relative humidity	%
со	Carbon monoxide concentration	ppm
lpg	Liquefied petroleum gas concentration	ppm
smoke	Smoke concentration	ppm
light	Light sensor (binary)	boolean
motion	Motion sensor (binary)	boolean

Table 1: Fields and types of the environmental sensor dataset.

- Missing values: Rows with missing values were removed in both InfluxDB and Oracle workflows.
- Timestamp conversion: The ts column was converted from String to a datetime format using pandas.to_datetime. In Oracle, it was further typed as TIMESTAMP WITH TIME ZONE.
- Boolean values: The fields light and motion were converted to bool for InfluxDB, but stored as string in Oracle to simplify schema compatibility.
- Numeric values: All gas and temperature fields were explicitly cast to float (InfluxDB) or DOUBLE PRECISION (Oracle).

Schema Implementation

The telemetry dataset was first cleaned and transformed before being loaded into both database systems.

In Oracle, the data was imported into a structured relational table with typed columns. Timestamps were stored as TIMESTAMP, numeric sensor values as NUMBER, and boolean states (light, motion) as strings due to the lack of native boolean support. Each row was assigned a unique ID. The data was inserted into the table IOT_TELEMETRY_DATA using a batch insert query.

In InfluxDB, the same data was stored as time-series points in the measurement iot_telemetry. Each point included a high-precision timestamp, a device tag, and multiple sensor fields such as humidity, temperature, and gas values. Fields were cast to floating-point or boolean types. A dedicated bucket named iot_telemetry_data was created to hold the measurement.

Schema Visualization

Figure 1 shows the InfluxDB structure. Figure 2 illustrates the Oracle table layout.

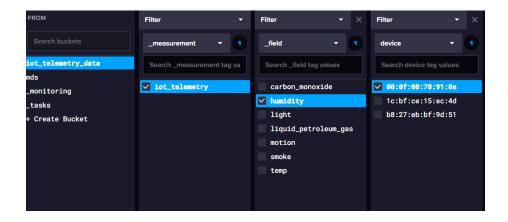


Figure 1: InfluxDB measurement schema with tags and fields.

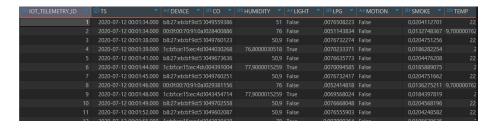


Figure 2: Oracle relational table for telemetry data.

Summary

The dataset combines continuous variables, binary states, and a small amount of missing values. These were cleaned and typed appropriately before loading. The resulting data structure is well-suited for evaluating different database models in time-series analytics.

3 Architecture Comparison

3.1 InfluxDB: Time-Series Architecture

InfluxDB uses column-oriented storage for high write throughput and fast time-based queries. Data is organized into measurements with indexed tags and unindexed fields, each tied to a timestamp [2]. On top Influx in the major release version 2 comes with it's own query language called Flux and a standard SQL Query language. Flux is a query language designed for working with time stamps and allows read operations with relative time windows [3].

- Measurement: A named collection of related time-series data, similar to a table in SQL. It groups points of the same type (e.g., "temperature").
- Tags: Key-value pairs used as indexed metadata. Tags provide fast filtering and grouping (e.g., sensor="UUID").
- Fields: The actual data values for a point (e.g., temperature=22.5). Fields are not indexed and can vary in type.
- **Point**: A single record composed of a timestamp, one measurement name, zero or more tags, and one or more fields. It represents one data observation in time.

3.2 Oracle Database: Relational Architecture

Oracle 23ai Free Database is a row-based relational system. It supports complex SQL, transactions, and strong consistency by using the System Global Area (SGA) and background processes to manage memory and I/O [4]. The SGA is a block of shared memory where Oracle keeps data and SQL code so queries run faster and the disk is accessed less often.

3.3 Architectural Differences

Purpose and Specialization Oracle and similar SQL databases serve general applications transactions like standard SQL and strong consistency. InfluxDB is built for high volume, append-only time-series data with fast ingestion and time-based aggregations [3].

Time as Primary Key In InfluxDB, each point's timestamp is mandatory and acts as the primary key, optimizing storage and queries by time. In SQL databases, time is just another column and needs separate indexing for efficient time-based queries [3].

Schema and Flexibility SQL databases require a fixed schema before inserting data, and changes need migrations. InfluxDB infers schema on write, allowing new fields without migration; this speeds up development but can lead to inconsistent data [3].

Data Model

- InfluxDB: Measurements (like tables), tags (indexed), fields (values), points (timestamped records).
- Oracle: Tables with fixed columns, manual indexes, and defined data types.

Query Capabilities SQL supports JOINs, subqueries, window functions, and transactions. InfluxQL offers basic SELECT queries without JOINs; Flux adds joins and transformations but remains optimized for time-series analytics [3].

Data Operations SQL fully supports Create, Read, Update, Delete with constraints. InfluxDB is append-only: updates overwrite points with identical timestamps/tags, and deletes apply only to time ranges or entire series [3].

Summary InfluxDB is used for write-heavy, time-based workloads with flexible schema and independent scaling but lacks full relational features. SQL databases are versatile and support complex queries and transactions but are less efficient for large-scale data.

4 Theoretical Comparison: InfluxDB vs. Oracle SQL

4.1 CAP Theorem

The CAP theorem, states that a distributed system cannot guarantee all three of the following properties at the same time [5]:

- Consistency (C): All nodes see the same data after a write.
- Availability (A): Every request gets a response, even if some data is delayed or stale.
- Partition Tolerance (P): The system continues to function even if network failures split the system into disconnected parts.

InfluxDB and CAP InfluxDB combines two subsystems with different CAP characteristics [6]:

- Metadata layer: Responsible for setting up the cluster and managing shards. It uses the Raft algorithm and follows the CP model (Consistency and Partition Tolerance). This ensures that all nodes agree on every change, but if the network splits, updates may be paused.
- Data layer: Handles data inserts and queries. It follows the AP model (Availability and Partition Tolerance), so it remains available even during network splits. It uses adjustable consistency levels, hinted handoff, and anti-entropy repair to make sure data becomes consistent over time.

Aspect	InfluxDB (Time-Series)	SQL Databases (General)
Design Purpose	Optimized for time-series data, high write	Designed for general-purpose data, trans-
	speed, time-based queries	actions, structured queries
Primary Key	Timestamp (with tags) as fixed and central	Any column can be used as primary key;
	key	timestamp optional
Schema Flexibility	Dynamic schema, fields defined at write	Static schema, must be predefined and con-
	time	sistent
Data Model	Measurements, tags, fields, points	Tables, columns, rows, primary/foreign
		keys
Indexing	Tags are indexed automatically; fields are	Indexes must be defined manually on any
	not	column
Query Language	InfluxQL (limited), Flux (functional, time-	Full SQL (rich query language with JOINs,
	focused)	subqueries, etc.)
Joins	Not supported in InfluxQL; limited in Flux	Fully supported across tables
CRUD Support	Focus on Create and Read; limited Up-	Full Create, Read, Update, Delete support
	date/Delete	
Tag and Field Operations	Tags cannot be renamed/deleted; fields can	Columns can be changed, renamed, or
	be overwritten only	dropped
Performance	High insert and query speed for time-series	Slower for time-series without optimiza-
		tion; better for complex queries
Best Use Cases	IoT, monitoring, metrics, logging, real-	Business systems, transactions, reporting,
	time analytics	relational data

Table 2: Comparison between InfluxDB and SQL Databases

Oracle SQL and CAP Oracle SQL databases typically follow the CA model (Consistency and Availability). They prioritize consistency and availability under normal conditions. During a network partition, they may block access or stop services until the issue is resolved. Oracle systems provide strong ACID guarantees and are usually deployed in tightly connected environments where Partition Tolerance is not the main concern.

4.2 BASE vs. ACID Philosophy

The BASE model is used in many NoSQL and time-series databases [7]. It stands for:

- Basically Available: The system remains responsive, even if some nodes fail
- **Soft State:** The system state may change over time, even without new input.
- Eventually Consistent: All nodes will become consistent after some time.

InfluxDB and BASE InfluxDB follows the BASE philosophy:

- Data is always accepted and written quickly (Basically Available).
- In the short term, the state may be inconsistent (Soft State).
- Through background processes like hinted handoff and Merkle Tree-based anti-entropy, consistency is achieved over time (Eventually Consistent).

Updates and deletes in InfluxDB require strong consistency settings or post-processing. Most operations are insert-only, and the system is designed to operate under temporary inconsistencies.

Oracle SQL and ACID Oracle databases follow the classic ACID model:

- Atomicity: Transactions are all-or-nothing.
- Consistency: The database always moves from one valid state to another.
- Isolation: Parallel transactions do not interfere.
- Durability: Once committed, data remains stored.

Oracle ensures immediate consistency. It does not follow BASE principles. Updates and deletions are executed in a fully synchronized and consistent way.

This theoretical comparison shows that InfluxDB and Oracle SQL follow different philosophies. InfluxDB is optimized for high availability and scale, accepting temporary inconsistencies. Oracle SQL focuses on strict data integrity and consistent transactions, even if availability or flexibility is limited during failures.

5 Experiment and Observations

5.1 Experiment Setup

To ensure a fair and reproducible comparison, both database systems Oracle Database 23ai Free and InfluxDB 2.7 were installed using Docker containers. This allowed us to control the execution environment and avoid side effects from background processes or prior system states.

Each performance test was executed inside a fresh container instance. Before running each query group, the container was restarted and caches were cleared. This fresh cache scenario helps simulate first time access and reduces any advantage from internal memory optimizations. All analyses were performed using Python notebooks that were executed under identical conditions for both systems. On top the experiments were run on two different systems by the authors to ensure independence.

5.2 Experiment

For the performance study, we executed five analytical queries on both databases. The queries represent common patterns in time-series workloads: aggregation, extreme value detection, and compound metric computation. The curated queries also differ in complexity to further identify strengths and weaknesses of the databases.

- Q1 Average humidity per device *Task*. Compute the mean of humidity for each device (GROUP BY device). *Motivation*. Tests per-device roll-ups over the full time span.
- Q2 Maximum temperature (global) *Task.* Return the highest value of temp across all devices and timestamps. *Motivation*. Exercises a global extreme value search over time.
- Q3 Worst air-quality score per device Task. Derive an air-quality index AQI = co + 1pg + smoke and report the maximum AQI per device.

 Motivation. Combines multiple columns and stresses aggregation.
- Q4 Temperature-Humidity Ratio (daily) Task. Calculate the average of temp/humidity for each day. Motivation. Involves arithmetic over two fields and grouping by time.

Q5 – Temperature-Humidity Ratio (per minute) Task. Calculate the average of temp/humidity per minute. Motivation. Evaluates fine-grained time grouping with calculation.

Each query (Q1–Q5) was executed 5 times on both systems after container startup. No other workloads were active. Query runtimes were measured with Python timing functions and averaged to reduce fluctuation.

5.3 Execution Results

Table 3 shows the average runtime for each query on both systems. Values are in seconds and reflect cold start performance under identical conditions.

Query	Oracle DB (sec)	InfluxDB (sec)
Q1 – Average humidity	0.103	0.251
Q2 – Maximum temperature	0.033	0.033
Q3 – Worst air-quality score	0.084	1.729
Q4 – Temp/Humidity Ratio (daily)	0.129	2.440
$\mathrm{Q5-Temp/Humidity\ Ratio\ (min)}$	0.443	3.038

Table 3: Average query execution time (in seconds).

5.4 Preliminary Observation

The results show that Oracle DB outperforms InfluxDB in most cases. While both systems show equal performance for the global maximum temperature query (Q2), Oracle shows faster execution in complex analytical queries (Q3–Q5). InfluxDB performs slower, especially for queries with fine time granularity and arithmetic operations.

5.5 Interpretation of Results

The experiment shows that Oracle Database was faster than InfluxDB in almost all queries. This result is surprising and goes against our initial assumption that a time-series database like InfluxDB would perform better in this context.

Unexpected outcome: Oracle is faster. We expected InfluxDB to have better performance because it is designed for time-series workloads. However, Oracle SQL was not only faster in simple queries but also in more complex ones (e.g., Q3–Q5).

5.6 Investigation of Performance Differences

At this stage, we investigated why Oracle Database outperformed InfluxDB in our experiment. Because Oracle is closed source, we cannot examine its internal implementation in detail. However, several factors may explain its superior speed:

- Maturity and Optimization: Oracle has been under active development for decades. Over this time, engineers have refined indexing schemes and implemented advanced caching strategies to reduce query latency.
- **High-Performance Implementation:** The Oracle backend is written in optimized languages such as C++ and assembly. These languages allow tight control over memory and processor usage, which can yield faster execution.
- InfluxDB's Current Stack: In contrast, InfluxDB 2.x relies heavily on Node.js, a higher-level runtime that, while flexible, generally runs slower than lower-level languages.
- Future Directions: InfluxData has announced plans to rewrite the entire code base in Rust. This change could improve performance in future releases and potentially narrow the gap with Oracle.

5.7 Benefits of Using InfluxDB

Despite the slower performance, InfluxDB offers several advantages for time-series use cases:

- It has a built-in web UI that makes it fast and easy to manage the database.
- Users can filter and aggregate and visualize data based on time in the UI which helps with understanding the data.
- Tasks: InfluxDB is able to create automatic tasks. They can be used for recurrent tasks like filtering out only the most important by statistical methods and more.
- Retention Time: Buckets can have fixed retention therefore automatically delete all the data after a specific time window.
- Nano seconds: Time Stamps can be saved up to Nano seconds which allow for detailed investigation especially for highly sensible IoT data.
- Flexibility and customization: InfluxDB allows for creating custom data schemas and types allowing to tailor the database to the project requirements [8].

• Open Source: Due to it's open source nature, InfluxDB is especially interesting for smaller comapanies with less budget.

Analyzing time-series data is not always just about time performance. There are many benefits that InfluxDB comes with by default which makes working and understanding Big Data easy and fast.

6 Conclusion

This study compared InfluxDB 2.7 and Oracle Database 23ai Free for storing and querying IoT telemetry data. Both systems were evaluated under controlled conditions using real sensor data and three representative analytical queries.

The experimental results indicate that Oracle Database outperforms InfluxDB in overall query execution time. Its mature SQL engine and optimized relational model make it well suited for complex analytical tasks on large datasets. In contrast, InfluxDB offers a complete and useful ecosystem that simplifies the understanding, management, and automation of time-series data for end users. Although execution speed is important, the functionality and ecosystem support provided by a database are equally critical. In this respect, InfluxDB shows clear advantages for business-oriented applications.

The upcoming major release of InfluxDB (version 3) seems promising because it is built on a new technology stack written in Rust. In future work, it would be interesting to evaluate InfluxDB 3 experimentally in order to quantify any latency improvements resulting from this rewrite.

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