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Real Time Mobility Intelligence: Evaluating Kafka Based Pipelines in Global Smart Transit Systems

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ABSTRACT: Real-time streaming architectures are redefining the landscape of urban transit analytics by enabling low latency, data driven decision making. This study evaluates and compares the real time data processing capabilities of public transit systems in London, New York, and Singapore. The objective is to determine how architectural choices, data freshness, and machine learning integration influence key performance indicators such as latency, ETA accuracy, and anomaly detection. The methodology involves a multi city case study, where Kafka based pipelines integrated with Apache Flink and Spark were assessed for ingestion, processing, and service delivery. Datasets included GTFS Realtime, SIRI feeds, and contextual APIs (e.g., speed bands and crowd density). Metrics for evaluation included feed latency, mean absolute error (MAE) and root mean square error (RMSE) for ETA, and response times for anomaly detection. The results demonstrate that Singapore's transit system outperformed its counterparts with the lowest latency (~12s), highest ETA accuracy (MAE = 18s; RMSE = 25s), and superior anomaly detection via multi sensor fusion. London and New York, while technologically robust, faced constraints due to longer feed update intervals and integration complexities. Kafka ML's online learning enhanced model adaptability, significantly reducing ETA prediction errors across dynamic conditions. Furthermore, stress testing revealed Singapore's architecture as the most resilient under peak load. The study concludes that the effectiveness of real-time urban transit systems depends on harmonizing streaming infrastructure... Singapore's architecture may serve as a potential reference model for other cities, while recognizing contextual differences in implementation. Singapore's architecture offers a scalable template for other cities. Ethical considerations, including data governance and passenger privacy, are essential for sustainable implementation.

Keywords: Real Time Analytics, Transit ETA, Kafka, GTFS Realtime, Anomaly Detection, Smart Cities, Streaming Architecture.

INTRODUCTION

Urban transit systems have undergone significant transformation driven by the proliferation of smart city initiatives and advancements in data processing technologies. As demand grows for efficient and responsive transportation networks, the capacity to analyze and act upon real-time information has become increasingly critical. Traditional batch processing architectures, while historically effective in handling large volumes of data, have proven insufficient in addressing the real time demands of dynamic transit environments. Their inherent latency and dependence on pre collection cycles hinder prompt decision making, thereby affecting operational reliability and public trust (Kang et al., 2017; Sallapalli, 2024).

This backdrop has prompted a shift toward streaming data architectures particularly those utilizing platforms such as Apache Kafka, Apache Flink, and Apache Spark. These frameworks allow for immediate ingestion and processing of transportation data, offering enhanced responsiveness and analytical precision. Kafka, for instance, leverages a publish-subscribe model optimized for high-throughput data streams. Flink supports continuous event-driven computations with sub-second latency, while Spark balances micro-batch and stream processing to deliver scalable insights in near real-time (Ding et al., 2020; Folorunsho et al., 2024). These capabilities collectively underpin a new generation of transit technologies that are capable of adaptive, low latency operations.

In parallel, the standardization of real time transit data has emerged as a vital enabler for interoperability and data quality. The General Transit Feed Specification Realtime (GTFS RT) and Service Interface for Real time Information (SIRI) protocols facilitate structured delivery of vehicle positions, delays, and service disruptions. GTFS RT has become the de facto global standard for public transit, offering consistent formatting and minimal integration overhead. SIRI, while more detailed and interoperable across platforms, entails a steeper implementation curve. Their adoption has proven instrumental in improving ETA prediction and enhancing passenger experience through reliable, live transit information (Bibri, 2021; Silva et al., 2018).

Feed freshness and system latency are crucial metrics in determining the effectiveness of real time data infrastructures. Freshness indicates how recent the data is, whereas latency captures the total delay from data generation to its actionable use. Delays in either dimension can severely impact ETA accuracy and incident detection. For example, a 30 second lag in data refresh could lead to major discrepancies in bus arrival forecasts, ultimately disrupting commuter expectations and operational planning (Ali et al., 2022).

Advancements in real time data handling have also catalyzed the integration of machine learning (ML) into public transit systems. ML algorithms continuously refine ETA models by ingesting live traffic patterns, historical datasets, and contextual signals such as passenger density or weather conditions. These learning systems support predictive adjustments that enhance accuracy and reliability. Techniques such as regression, time series forecasting, and reinforcement learning allow models to evolve in real time, aligning predictions with shifting transit dynamics (Thanasas & Kampiotis, 2024).

Beyond technical enhancements, real time analytics play an expanding role in shaping urban policy and smart city governance. Data driven strategies enable cities to monitor traffic flows, manage public infrastructure, and implement responsive services. For instance, adaptive traffic signal systems can optimize throughput based on real time vehicle location data, reducing congestion and emissions. Additionally, predictive analytics derived from transit data inform long term investments in urban infrastructure, facilitating sustainable growth and equitable access ((Kitchin, 2016; Munshi et al., 2023).

Despite the evident progress, disparities remain in the implementation quality and outcomes of streaming architectures across cities. While some municipalities, such as Singapore, have achieved low latency, high accuracy operations through comprehensive API ecosystems and frequent data refresh rates, others contend with legacy systems and integration challenges. These differences necessitate a comparative approach to assess the operational efficacy of streaming pipelines across various urban contexts.

This study addresses that need by evaluating the streaming pipeline performance of three smart cities London, New York, and Singapore with a focus on transit ETA prediction and anomaly detection. It examines how architecture design, feed standards, data richness, and machine learning contribute to system responsiveness and accuracy. The study also offers a methodological framework for benchmarking real time data infrastructures in public transit, aiming to guide future deployments toward higher efficiency, scalability, and service quality.

METHOD

This study adopts a comparative case analysis approach to evaluate the streaming pipeline performance of three urban transit systems Transport for London (TfL), Metropolitan Transportation Authority (MTA) in New York, and Singapore's Land Transport Authority (LTA DataMall). The methodology integrates architectural modeling, data acquisition, metric benchmarking, and applied literature insights to assess pipeline efficiency, real time responsiveness, and ETA accuracy.

The selected cities were chosen for their mature, open access real time transit data systems. London and New York utilize a combination of GTFS Realtime and SIRI feeds, while Singapore's LTA offers rich APIs with sub 10 second refresh rates. Each city represents a different maturity level and data architecture, enabling comparative analysis.

The architectural pattern follows a modified Kappa model, designed for continuous stream processing without batch layers. Each pipeline consists of four core components:

- Ingestion Layer: Kafka topics structured by vehicle type, route, and feed class (e.g., trip updates, vehicle positions). Kafka's publish subscribe model supports high throughput, asynchronous data flow (Hassan et al., 2022).
- Stream Processing Layer: Apache Flink and Spark Structured Streaming process incoming data via sliding/tumbling windows, join with static GTFS data, and compute ETA predictions. Kafka ML is used to incorporate real time online learning, adjusting models based on live feed characteristics (Pourmoradnasseri et al., 2023).
- Storage Layer: RocksDB is used for high speed, embedded hot storage, while batch processed records are exported to a Data Lake for historical evaluation and reprocessing.

- Service/Insight Layer: Real time results feed into operator dashboards (for SLA and anomaly monitoring) and open APIs (for public ETA access and alert notifications).

To evaluate the pipeline's performance, we use four categories of metrics:

- Latency: Time delay from data generation to its actionable use.
- Feed Freshness: Update interval of real time feeds (e.g., TfL and MTA: 30s, LTA: ≤10s).
- ETA Accuracy: Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) of predicted vs. actual arrivals.
- Anomaly Detection Effectiveness: Capacity to identify headway gaps or speed anomalies using stream aggregation.

Dataset Collection and Configuration

- TfL: Countdown/iBus API providing vehicle position and arrival estimates refreshed every 30s.
- MTA: GTFS RT and SIRI APIs for trip updates, vehicle positions, and stop monitoring; augmented by 2024 Bus Segment Speeds dataset.
- LTA DataMall: Bus Arrival, Speed Bands, Crowd Density APIs with sub 10s freshness.

Data were collected over two week intervals for each city, capturing weekday and weekend patterns. Feeds were stored and replayed for benchmarking under simulated stress scenarios (e.g., peak hour data bursts).

Architectural Enhancements and Best Practices

Based on literature, several optimizations were embedded:

- Edge Processing: Simulated via MEC node emulation to reduce latency.
- Windowing and Batching: For load reduction and throughput maximization.
- Asynchronous Communication: Applied at ingest and API layers to maintain pipeline responsiveness.
- Monitoring: Continuous logging and stream metrics for real time anomaly detection.

This layered and optimized architecture supports reproducible, scalable analysis of streaming performance across urban mobility systems.

RESULT AND DISCUSSION

This chapter presents the empirical outcomes of the benchmarking tests performed on three urban mobility systems London (TfL), New York (MTA), and Singapore (LTA) based on the streaming pipeline architecture described earlier. The performance indicators assessed include feed freshness, latency, ETA prediction accuracy, and anomaly detection effectiveness.

Feed Freshness and Latency

City	Feed Type	Feed Update Interval	End to End Latency
London	GTFS RT (Countdown/iBus)	30 seconds	~33 seconds
New York	GTFS RT + SIRI	30 seconds	~32 seconds
Singapore	LTA DataMall APIs	≤10 seconds	~12 seconds

Optimized ingestion pipelines using Kafka and real time processing frameworks (Flink, Spark) significantly mitigated the delays observed in traditional batch processing systems. Research emphasizes that these stages, when designed with asynchronous data flow and event driven models, can maintain sub 30s system responsiveness (Waltemate et al., 2016).

ETA Prediction Accuracy

City	MAE (seconds)	RMSE (seconds)
London	40	58
New York	30	42
Singapore	18	25

ML models such as GBM and LSTM were evaluated in stream mode using Kafka ML to continuously retrain based on real time inputs. Multi source data fusion significantly improved prediction reliability by combining GPS, historical trends, and density metrics (Choi et al., 2020).

Anomaly Detection Performance

City	Detection Method	Effectiveness
London	Headway gap detection via sliding window	Moderate
New York	Segment speed drop	High
Singapore	Fusion of crowd density & speed anomaly	Very High

Windowing strategies (sliding/tumbling) enabled timely detection of service irregularities. These approaches, validated in past studies, are highly effective when tuned with appropriate thresholds and sampling frequencies (Kuiper & Bekooij, 2017).

Pipeline Robustness and Scalability

Stress tests during simulated peak load conditions revealed that all three pipelines scaled horizontally under Kafka without degradation. However, only Singapore's system sustained sub 15s latency under peak due to its minimal reliance on centralized batch processing and higher update frequency. Real time monitoring via logs and pipeline metrics proved essential for maintaining throughput and reliability (Munshi et al., 2023).

Overall, the results confirm that a combination of high frequency feeds, modular stream architectures, and ML based analytics significantly enhances the performance of real time transit systems.

The evaluation of streaming pipeline performance across three prominent global urban transit systems namely London, New York, and Singapore reveals several nuanced patterns and relationships among architectural choices, data standardization, real time update frequency, and overall system responsiveness. This analysis provides insights into how the integration of modular, high frequency, and adaptive streaming infrastructures can dramatically impact both the quality of transit services and commuter satisfaction. As more cities transition toward smart mobility solutions, real time analytics will remain a cornerstone in delivering reliable, efficient, and scalable public transport systems.

Among the most immediate and measurable performance metrics is latency, which defines the time lag between data generation and actionable output. Comparative latency results across the three cities establish a strong relationship between feed freshness and total system responsiveness. Singapore's LTA DataMall ecosystem emerged as the leader, with latency as low as 12 seconds considerably lower than London and New York, both of which maintained average latencies above 30 seconds. These figures correspond directly with their respective update frequencies: while TfL and MTA primarily operate on 30 second GTFS RT or SIRI update cycles, LTA DataMall delivers data at ≤10 second intervals. These findings strongly support prevailing academic perspectives that endorse high frequency feed updates and event driven architectures as foundational elements for minimizing latency (Severino et al., 2023; Sreekanti et al., 2020).

Additionally, the influence of mobile edge computing (MEC) on latency performance is worth deeper exploration. Although not fully operationalized in any of the three evaluated systems, theoretical literature and early stage deployments suggest that integrating MEC nodes could offload latency sensitive computations such as vehicle rerouting or emergency incident alerts from centralized servers to edge devices. In such configurations, MEC allows for data processing closer to the point of capture, significantly improving time to response while reducing network overhead (Alamri, 2023; Wilbur et al., 2021). The potential benefits of such architectural enhancements cannot be understated, particularly in cities with high density transit networks that demand rapid decision cycles.

ETA prediction accuracy represents another critical domain of evaluation. Singapore again achieved superior outcomes with the lowest Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), measuring 18 and 25 seconds respectively. This performance stems largely from its ability to combine multiple data streams including speed bands, crowd density, and GPS positioning into a unified analytics framework. The integration of machine learning models such as Gradient Boosting Machines (GBM) and LSTM networks, deployed via Kafka ML, enabled real time retraining and adaptation to emerging traffic patterns. In comparison, New York, with its dual integration of GTFS RT and SIRI, achieved intermediate accuracy, while London's relatively older infrastructure and single source data architecture resulted in higher prediction errors. The literature consistently supports the superiority of online learning models over static ones in dynamic environments like urban transit systems (Chaves et al., 2023). Online models demonstrate better adaptability and accuracy by continuously incorporating live input data, unlike static models that rely on outdated, historical training data.

Anomaly detection performance also illustrated significant differences among the cities. London employed Flink based headway gap detection using sliding windows, which, while functional, exhibited only moderate effectiveness. New York's method utilized segment speed drops, improving detection reliability. Singapore implemented a dual signal anomaly detection framework combining crowd density and speed anomaly analysis, achieving the highest performance. This confirms research emphasizing that multi source, high resolution data streams are essential for accurate real time incident analytics (Becker et al., 2020). Furthermore, employing tumbling and sliding windows in platforms like Flink and Spark facilitates continuous anomaly tracking, enabling swift detection of bottlenecks, delays, and disruptions.

Beyond predictive and detection capabilities, the study underscores the importance of architectural robustness and system scalability. During simulated stress conditions, all three pipelines successfully scaled under Kafka's horizontal infrastructure, yet only Singapore's configuration maintained sub 15 second latencies during peak load. This performance advantage is tied to its architectural simplifications, pre aggregated APIs, minimized reliance on batch processing, and real time monitoring systems. Best practices such as asynchronous communication, fine grained resource scaling, and efficient state management played a key role in preserving pipeline responsiveness (Munshi et al., 2023).

The evaluation also brings attention to trade offs in data standardization. GTFS RT and SIRI serve as the two prevailing standards in the industry, each with unique strengths and weaknesses. GTFS RT is widely adopted due to its simplicity and ease of integration, making it ideal for agencies with limited technical infrastructure. However, it lacks the depth and granularity of SIRI, which supports detailed vehicle status, occupancy, and service alerts (Kyriakakis et al., 2021). New York's attempt to integrate both standards exemplifies the challenges in achieving data consistency and interoperability. Singapore's streamlined GTFS RT based approach suggests that simplified yet reliable standards can deliver competitive advantages, especially when paired with robust architectural and analytical enhancements.

Equally important are the governance and ethical dimensions of real time transit data usage. With the proliferation of real time data collection, concerns about privacy, surveillance, and algorithmic bias become increasingly salient. Sensitive data such as GPS traces and passenger density raise questions regarding data ownership, consent, and potential misuse (Carnero et al., 2021). Without strong governance mechanisms and transparent data policies, public trust in transit systems may erode. Furthermore, algorithmic decisions especially those using biased training data risk exacerbating inequalities in service provision. Addressing these issues requires ethical design principles and the inclusion of fairness aware analytics, ensuring that advancements in real time mobility do not come at the cost of societal equity (Patil et al., 2022).

Ultimately, the findings from this study confirm that the performance of real time streaming pipelines is influenced not by a single factor but by the dynamic interplay between technical, organizational, and contextual elements. Singapore's exemplary performance serves as a benchmark and reinforces the concept that highly adaptive, context rich systems with continuous learning capabilities and well structured data streams provide the best outcomes. The successful convergence of event driven architecture, low latency processing, ML enhanced prediction, and ethical data stewardship represents a new frontier in urban mobility. As more cities strive to align with smart city objectives, the practical frameworks and results shared in this study offer a scalable blueprint for implementing next generation real time transit systems.

CONCLUSION

This study evaluated real-time streaming pipeline performance in the transit systems of London, New York, and Singapore, emphasizing how architectural design, feed standardization, and data richness influence responsiveness, ETA accuracy, and anomaly detection. The comparative results highlighted that Singapore's system achieved superior performance due to high-frequency updates, integrated contextual data, and modular Kafka–Flink pipelines.

The analysis further revealed that online learning models significantly enhance adaptability compared to static ETA approaches, ensuring more accurate predictions under dynamic traffic conditions. Stress tests underscored the importance of efficient state management, asynchronous processing, and observability features, particularly in maintaining resilience during peak loads. Governance and ethical considerations, including privacy and algorithmic fairness, remain critical to sustaining public trust in smart mobility systems.

In conclusion, the findings demonstrate that high-performing transit analytics emerge from the synergy of real-time streaming architectures, standardized data feeds, machine learning integration, and ethical governance. While Singapore offers a valuable reference model, future research should extend toward mobile edge computing, federated learning, and cross-border interoperability frameworks to further advance sustainable and equitable smart transit ecosystems.

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