A cross-platform data mart synchronization model for high availability in dual-cloud architectures

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Abstract

In the evolving landscape of enterprise data management, dual-cloud architectures have become a strategic choice to enhance redundancy, compliance, and vendor flexibility. However, ensuring high availability and consistent data synchronization across heterogeneous cloud platforms poses significant technical challenges, particularly for distributed data marts supporting critical analytical workloads. This paper presents a comprehensive, platform-agnostic synchronization model designed to address these challenges by harmonizing disparate storage engines, replication protocols, and metadata schemes. The proposed layered architecture incorporates real-time Change Data Capture mechanisms, bidirectional synchronization logic, and advanced conflict resolution strategies to maintain near-real-time data consistency. Embedded monitoring, automated recovery workflows, and governance controls further strengthen system reliability and compliance. The model facilitates seamless failover and resilience against cloud-specific outages and regional failures, while optimizing operational efficiency through incremental sync and smart batching. By bridging theoretical foundations with practical implementation considerations, this work advances the state of cross-cloud data mart synchronization and supports modern multi-cloud data strategies. Future research directions include AI-enhanced conflict resolution and empirical validation of synchronization performance, promising to extend the model's applicability and robustness in dynamic data environments.

Keywords: dual-cloud architecture, data mart synchronization, change data capture (cdc), high availability, conflict resolution, multi-cloud data governance

1. Introduction

1.1 Background

The adoption of multi-cloud strategies has become a defining trend among enterprises aiming to optimize costs, enhance fault tolerance, and avoid vendor lock-in [1, 2]. In parallel, data marts have emerged as essential components for departmental and line-of-business analytics, offering tailored, performance-optimized data stores to meet diverse user needs [3, 4]. These marts enable decentralized data access, improved query responsiveness, and specialized data governance. However, as organizations distribute their workloads across two or more cloud platforms, ensuring data availability and synchronization becomes increasingly complex [5-7]. Dual-cloud architectures, such as combinations of AWS and Azure, or GCP and Oracle Cloud, pose unique challenges in harmonizing data marts, especially when maintaining consistent and timely data across different geographic regions and infrastructure environments [8, 9].

Availability, consistency, and latency are fundamental concerns in these dual-cloud settings. Ensuring that users access reliable and up-to-date data across clouds is critical for business continuity, decision-making, and regulatory compliance. Variations in network latency, disparate storage models, and differences in security policies exacerbate synchronization challenges [10, 11]. Consequently, the concept of synchronized data marts arises as a robust solution, enabling fault-tolerant, near-real-time replication and alignment of data. This synchronization ensures continuous availability, reduces downtime, and supports resilient analytical workflows that are not bound by the limitations of a single cloud provider [12, 13]. Synchronized data marts also support disaster recovery and geo-redundancy by creating mirrored data environments across clouds. This multi-cloud mirroring protects against platform-specific outages or regional failures and enhances the scalability of analytical operations. Given the growing reliance on analytics-driven strategies, building reliable cross-cloud synchronization mechanisms is paramount for organizations seeking agility, robustness, and uninterrupted access to critical data assets.

1.2 Problem Statement

Despite the strategic advantages of multi-cloud deployments, maintaining real-time consistency across cloud-specific data marts remains a formidable challenge. Each cloud provider offers proprietary storage engines, replication protocols, and metadata management systems, creating a heterogeneous environment that complicates seamless data synchronization [14]. This heterogeneity introduces incompatibilities at multiple layers, ranging from differing data formats and schema evolution mechanisms to inconsistent transactional guarantees and latency profiles. These incompatibilities hinder the ability to synchronize data marts efficiently and reliably in near real time [15, 16].

Existing solutions often rely on vendor-specific replication tools or batch synchronization processes that fail to address the dynamic needs of modern analytics. Many current approaches lack the flexibility to handle bidirectional synchronization, conflict resolution, or tuning of consistency guarantees, especially in environments where data changes rapidly [17, 18]. Additionally, metadata and lineage information are frequently siloed within individual clouds, impeding effective cross-platform governance and auditability. The lack of unified synchronization frameworks that abstract away cloud-specific peculiarities creates operational complexity and increases the risk of data drift, stale reports, and compliance violations [19-21].

This gap in standardized, platform-agnostic synchronization models for cross-cloud data marts limits enterprises' ability to fully realize the benefits of multi-cloud resilience and availability. There is a pressing need for frameworks that not only bridge storage and protocol differences but also provide robust monitoring, conflict management, and recovery capabilities. Addressing these challenges would enable enterprises to synchronize data marts consistently and efficiently, ensuring dependable analytics regardless of the underlying cloud infrastructure.

1.3 Objectives

This paper aims to develop a cross-platform synchronization model that guarantees high availability and data consistency for data marts distributed across dual-cloud architectures. The primary objective is to design an architectural framework capable of harmonizing disparate cloud storage engines, replication mechanisms, and metadata models, thereby enabling fault-tolerant, near-real-time data synchronization. This framework seeks to support both event-driven and batch synchronization strategies, accommodating the diverse latency and consistency requirements typical of analytical workloads.

The paper's core contributions include a layered architectural design that encapsulates ingestion, staging, synchronization, orchestration, and governance layers, each addressing specific challenges inherent to dual-cloud synchronization. The model emphasizes mechanisms for conflict resolution, metadata harmonization, and failover readiness, ensuring operational continuity even amid cloud-specific service disruptions. By integrating monitoring and recovery workflows, the framework supports proactive management and auditability.

Anticipated benefits of the proposed model encompass improved failover readiness and minimized downtime through automated synchronization and recovery. It enables near-real-time alignment of data marts, facilitating consistent analytics and compliance across platforms. This work not only contributes a theoretical model but also provides a practical blueprint for enterprises pursuing resilient multi-cloud data architectures that balance availability, performance, and governance.

2. Conceptual and Technological Foundations

2.1 Data Marts and Analytical Workloads

Data marts are specialized, subject-oriented repositories designed to support focused analytical workloads within organizations [22, 23]. Unlike enterprise-wide data warehouses, data marts decentralize analytics by providing tailored datasets optimized for specific business units or domains such as sales, marketing, or finance. This decentralization enhances query performance and enables more agile, contextualized decision-making by delivering domain-relevant data directly to stakeholders [24, 25].

Typical analytical workloads on data marts involve complex queries, aggregations, and trend analyses that demand low latency and high availability. Timely access to accurate data is critical, as many business decisions hinge on up-to-date insights. As these workloads increase in volume and complexity, ensuring that data marts reflect the latest data states becomes a significant operational challenge [26, 27].

In multi-cloud and geo-distributed environments, data marts often contain partitioned datasets spread across regions or platforms to optimize local access and comply with data residency regulations. However, this distribution introduces latency challenges and complicates synchronization efforts [28, 29]. Delays in data replication can cause inconsistent query results across marts, undermining trust in analytics. Consequently, maintaining data consistency and minimizing synchronization latency are paramount to supporting effective, high-availability analytical services across organizational boundaries [30-32].

2.2 Dual-Cloud Architecture Characteristics

Dual-cloud deployments involve leveraging two distinct cloud service providers simultaneously, such as AWS paired with Azure or GCP combined with Oracle Cloud Infrastructure [33, 34]. Organizations pursue dual-cloud architectures primarily to enhance redundancy and fault tolerance, mitigate vendor lock-in risks, and meet diverse regulatory or compliance requirements that may mandate data locality or separation of duties [35, 36].

Each cloud platform presents unique compute and storage paradigms. For example, AWS offers S3 for object storage, while Azure provides Blob Storage, each with different APIs, security models, and performance characteristics. Similarly, identity and access management (IAM) differ across providers, requiring federated identity solutions or custom mappings to enable seamless cross-cloud authentication and authorization [37, 38].

Networking between clouds introduces additional complexities such as varied latency profiles, bandwidth constraints, and security policies. Identity federation mechanisms and API gateways become essential components, enabling secure, controlled access to services and data across the disparate platforms. These architectural variations must be carefully accounted for when designing synchronization models to ensure seamless interoperability, secure data flow, and consistent policy enforcement throughout the dual-cloud ecosystem [39, 40].

2.3 Synchronization Models in Distributed Systems

Synchronization in distributed systems revolves around ensuring data consistency, integrity, and availability across multiple nodes or platforms [41, 42]. Core concepts include eventual consistency, where all replicas converge over time; conflict resolution, which addresses inconsistencies arising from concurrent updates; and replication topologies, defining how data flows between sources and targets (e.g., master-slave, peer-to-peer) [43-45].

Different synchronization mechanisms serve various needs. Log-based replication captures changes as transaction logs, replaying them on target systems for fidelity. Event-driven synchronization uses messaging or event streams to propagate changes in near real-time, optimizing latency [46]. Delta-based approaches transmit only changed data segments to minimize bandwidth. Checkpointing periodically saves consistent data snapshots to facilitate recovery and reduce sync overhead [47, 48].

To effectively manage cross-platform data marts, synchronization layers must be platform-agnostic, abstracting away cloud-specific details while providing unified consistency guarantees and operational controls [49-51]. This abstraction allows synchronization logic to operate independently of underlying storage engines or APIs, improving portability, maintainability, and extensibility across diverse cloud environments. Building such a layer requires harmonizing metadata, conflict resolution policies, and transport mechanisms to deliver reliable, near-real-time data consistency in complex dual-cloud architectures [52, 53].

3. Proposed Synchronization Model

3.1 Architectural Overview and Design Layers

The proposed synchronization model adopts a layered architecture to systematically manage the complexities of cross-platform data mart synchronization in dual-cloud environments [54, 55]. The architecture is composed of five core layers: ingestion, staging, synchronization orchestrator, data marts, and replication controller. The ingestion layer interfaces with data sources and pipelines, capturing real-time and batch changes from operational databases or upstream systems. Data then moves into the staging layer, where raw data is temporarily held and pre-processed for consistency checks, schema alignment, and metadata enrichment [56-58].

At the heart lies the synchronization orchestrator, responsible for coordinating data transfer, applying business rules, and triggering replication workflows. This layer interacts closely with message queues and schema registries that store versioned data models, ensuring that schema changes are harmonized across clouds. A metadata harmonizer component aligns differing metadata formats and nomenclature between platforms, enabling seamless data interpretation and transformation [59-61].

The final two layers represent the data marts themselves, targeted analytical repositories on each cloud, and the replication controller, which manages connectivity, data flow control, and error handling between them. Cross-cloud connectivity modules abstract cloud-specific APIs and network protocols, providing a uniform interface for replication tasks. This abstraction layer enables portability and adaptability, facilitating synchronization across heterogeneous storage systems without compromising consistency or performance [62, 63].

3.2 Synchronization Mechanisms and Logic

Synchronization within this model employs a bidirectional logic to support seamless, near-real-time data consistency between data marts. At its core is Change Data Capture (CDC), a technique that captures and records all data modifications at the source, including inserts, updates, and deletions. These changes trigger synchronization events, enabling the replication process to propagate updates incrementally and efficiently. Coupled with event-driven triggers, this mechanism reduces latency and minimizes unnecessary data transfers [64-66].

Given the inherent trade-offs in distributed systems, the model supports multiple consistency paradigms tailored to analytical workloads. While strong consistency ensures identical data views across marts, it may introduce latency. Alternatively, eventual consistency allows temporary divergence with guaranteed convergence, optimizing throughput. A tunable consistency approach enables stakeholders to balance strictness against performance based on specific use cases [67-69].

To resolve synchronization conflicts, arising when concurrent updates occur, the model incorporates strategies such as versioning, which tracks data revisions; timestamping, which orders changes chronologically; and source-of-truth heuristics, which designate authoritative systems for specific data domains. These mechanisms collectively ensure that synchronized data marts maintain integrity and accuracy even amid complex multi-cloud updates [70, 71].

3.3 Monitoring, Recovery, and Governance

Robust monitoring and observability are integral to the model, enabling continuous insight into synchronization health and performance. Embedded metric collectors gather data on replication latency, throughput, error rates, and resource utilization. These metrics feed into alert managers and sync state dashboards, providing real-time visibility to operations teams and enabling proactive issue detection [72-74].

To address failures such as transfer interruptions or schema mismatches, the model incorporates auto-recovery workflows. Upon detection of anomalies, automated processes attempt retries, schema reconciliation, or data rollbacks without requiring manual intervention. These workflows reduce downtime and ensure synchronization continuity across clouds [75, 76].

Governance is embedded through compliance controls like data tagging for lineage and sensitivity classification, audit logging for tracking changes and user actions, and Service Level Agreement (SLA) monitoring to enforce operational thresholds. Together, these governance measures promote transparency, accountability, and adherence to regulatory requirements, which are crucial for enterprise adoption in sensitive or regulated industries [77, 78].

4. Strategic and Operational Implications

4.1 High Availability and Fault Tolerance

The proposed synchronization model fundamentally enhances high availability by minimizing downtime and enabling continuous data accessibility across dual-cloud platforms [79, 80]. It supports hot-standby configurations, whereby data marts on one cloud can immediately take over analytical workloads should the counterpart fail or become unreachable. This seamless failover capability is critical in maintaining uninterrupted business operations and avoiding costly analytics outages [81, 82].

Failover handling is orchestrated using dynamic DNS routing, which reroutes data requests to the available cloud environment in real time. The model actively mitigates replication lag through incremental synchronization and prioritization of critical data streams, ensuring that failover environments are as up-to-date as possible. This reduces the risk of stale data during switchovers and sustains decision-making integrity [83-85].

The architecture is designed to be resilient not only to platform-specific outages but also to regional or zone-level failures, which are increasingly common in cloud environments. By distributing data marts across distinct geographic and cloud fault domains, the model guarantees that localized service degradations do not cascade into system-wide disruptions. This multi-layered resilience equips organizations with robust protection against diverse failure scenarios [86, 87].

4.2 Operational Efficiency and Consistency

Operationally, the model drives significant efficiency gains by automating synchronization tasks that traditionally required manual oversight or batch processing. Reducing the need for manual sync jobs and ad hoc data patching frees engineering resources and minimizes human errors. Automation also streamlines schema reconciliation and conflict resolution, accelerating issue resolution and reducing operational overhead [88, 89].

The model promotes data consistency across business intelligence platforms and federated query systems by maintaining synchronized, harmonized datasets in all data marts. This consistency ensures that analytics teams, regardless of cloud or region, operate on the same trusted data, eliminating discrepancies that can skew insights or lead to conflicting conclusions [90-92].

Latency improvements are achieved through incremental synchronization techniques that transmit only changed data segments rather than full datasets, minimizing bandwidth usage and replication delays. Smart batching mechanisms further optimize resource utilization by dynamically grouping changes based on network conditions and workload priorities. Together, these techniques support near-real-time data availability without compromising system performance [93-95].

4.3 Compliance, Auditability, and Cross-Team Collaboration

Compliance and auditability are essential in multi-cloud data environments, particularly where sensitive or regulated information is involved. The synchronization model incorporates robust data lineage tracking, which records the origin, transformation, and movement of data across clouds. This traceability provides transparency for auditors and regulators, simplifying compliance reporting and forensic investigations [64, 96, 97].

Unified data tagging and logging frameworks enable consistent classification of sensitive data elements according to regulatory standards such as HIPAA and GDPR. These controls ensure that privacy and security policies are uniformly enforced across platforms, mitigating compliance risks in distributed data marts [98, 99].

Furthermore, the model fosters cross-team collaboration by providing shared dashboards and governance layers accessible to data engineers, security officers, and business users alike. These tools facilitate transparent access management, change tracking, and operational insights, bridging organizational silos. By cultivating a culture of shared accountability and visibility, the model supports effective governance and accelerates the resolution of synchronization issues [100-102].

5. Conclusion

In today's increasingly complex data landscape, the need for robust, platform-agnostic synchronization models in dual-cloud environments is undeniable. This paper has demonstrated how distributed data marts, critical to organizational analytics, face persistent challenges related to availability, data consistency, and operational complexity across heterogeneous cloud platforms. The proposed synchronization model offers a comprehensive framework designed to overcome these challenges by providing a layered, abstraction-driven architecture that harmonizes cloud-specific storage, replication protocols, and metadata.

By supporting bidirectional, near-real-time synchronization and implementing conflict resolution mechanisms tailored to analytical workloads, the model effectively addresses critical concerns around data freshness and integrity. Its design enables enterprises to achieve high availability and fault tolerance, ensuring seamless failover and resiliency against cloud or regional failures. Furthermore, integrated observability and governance layers enhance operational clarity, compliance adherence, and auditability. Overall, the model aligns closely with the demands of modern data strategies focused on multi-cloud agility, resilience, and consistent analytics delivery.

The theoretical contribution of this work lies in its articulation of a platform-neutral synchronization framework that reconciles the disparate characteristics of cloud-native data stores into a unified operational model. It advances the field of cloud-native data architecture by providing an abstract yet implementable blueprint for cross-platform data mart synchronization, a topic that remains underexplored in academic literature.

Practically, the model serves as a valuable guide for enterprises seeking to enhance their data redundancy and regulatory diversification strategies by leveraging multiple cloud vendors. It facilitates seamless data replication and governance across clouds, which is crucial for organizations dealing with stringent compliance requirements and complex analytics demands. The model's integration with DevOps and DataOps principles promotes automation, continuous monitoring, and rapid recovery, making it a strong candidate for adoption within contemporary cloud operations and analytics workflows. Several promising avenues exist to extend this foundational model. Integration with real-time streaming data sources can enable synchronization of rapidly changing datasets and support more dynamic analytics scenarios. Synchronization of machine learning feature stores across clouds presents another emerging use case, requiring specialized handling of feature freshness and consistency.

The incorporation of artificial intelligence techniques to assist in conflict resolution and predict synchronization bottlenecks holds potential to further optimize system performance and reduce manual interventions. Empirical studies evaluating synchronization latency and Recovery Time Objectives (RTOs) would provide critical validation and refinement, enabling better quantification of model efficacy under diverse operational conditions. Such future work will deepen understanding and drive continuous innovation in multi-cloud data synchronization strategies.

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