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Original Article

Designing Hybrid ETL Pipelines for Multi-Cloud Integration

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Abstract - The growing popularity of multi-cloud infrastructures has led to the need for scalable and interoperable ways to integrate data that is distributed across several platforms. In this project, we outline the design and simulation of a multi-cloud integration ETL pipeline using Python. We train using generated data from public clouds such as, AWS, Microsoft Azure and GCP, into a single cloud-agnostic data warehouse with open source libraries like pandas, SQLite3 and matplotlib. The ETL system was architecture as a set of modules, including extraction, transformation, loading and performance monitoring. Scalability and resource usage were tested in three runs using graduated data volumes. The results indicate that the processing times were between 0.01 and 0.02 seconds but used a fairly constant memory size, ranging from 90.98 MB with 32 records to 91.41 MB for parsing of up to 864 records. These results validate the efficiency and stability of the pipeline, as well as its ability to account for multi-source data integration in a low computational burden. The work shows that local simulation of hybrid ETL systems is possible and gives a scalable and reproducible basis for deployment in real-world multi-cloud infrastructures to come. This work adds to the efforts on data interoperability, performance optimization and cloud-native ETL architecture design.

Keywords - Hybrid ETL pipeline; multi-cloud integration; Cloud data interoperability; Data transformation and warehousing; Python-based simulation; Data performance metrics; Scalability and efficiency; Digital twin optimization; Zero-ETL architecture; Cloud-native data engineering.

1. Introduction

The fast pace of multi-cloud adoption has redefined the way in which data is handled across different environments. Organizations are consuming workloads from multiple cloud providers such as AWS, Azure and Google Cloud to improve reliability and scalability. Nevertheless, this introduces difficulties regarding data transferability, standardization and compatibility. ETL (Extract-Transform-Load) processes are critical for integrating data from disparate sources into consolidated analytical systems. ETL architectures that are designed for single-cloud and on-premise do not provide the flexibility needed to perform hybrid multi-cloud integration. This paper describes and publishes the design and development of a ETL hybrid multi cloud framework using Python based simulation which is an in demand technology. The result, obtained using open source tools such as pandas, SQLite and matplotlib, is an application which successfully illustrates a scalable, transparent, low cost solution to playing data in. This is the next generation multi-cloud ETL deployment in a real enterprise.

2. Literature review

2.1. Evolution of ETL and Modernization of Data Pipelines

ETL (Extract Transform Load) systems are the building block of these application and warehousing integration tools. Its evolution from on-premise batch systems to cloud and real-time streaming architectures reflects the needs of enterprise analytics over time. In [1], Arul | Page 3 et al have provided with recent comparison of ETL tools such as AWS glue, Google cloud dataflow and Apache nify where three above mentioned ETL tools (cloud specific) & also how it fits in modern trend is described elaborately with detailed manner. He noted in his research that the latency, scalability and integration capabilities are new performance standards for ETL in big data environments. Since 2019, serverless function computing and event-driven architecture is reshaping ETL pipelines which can ingest and process data at near real-time that democratizes access to data on hybrid infrastructure.

This refresh follows an increase in the requirement for nimble data processing as the volume, velocity and variety of data being handled expands. Static ETL solutions are being replaced by modular, self-configuring transform frameworks [1]. And rather than trading off scalability to modernization, now you get both with more cost efficiency by utilizing autoscaling and distributed computing. The comparative results also reveals that open-source tools such as NiFi comes handy for flexibility, whereas proprietary cloud provider is able to offer managed scale and integration, which reflects a conflict of desire on the control over the system vs. ease of use.

2.2. Hybrid Optimization in Cloud-Based ETL Systems

ETL optimizations have been trending research topics, particularly about the performance bottlenecks of transformation and load stages. Dinesh and Devi [3] propose a hybrid optimization module integrating swarm intelligence along with tabu search algorithm for improving the performance of ETL in data warehouse issued over cloud environment. Their hybrid GWO–Tavu Search (TS) model is shown to reduce data dimensionality to a great extent and cluster the related data, hence reducing the redundancy and enhancing the efficiency of query response. The proposed GWO-TS hybrid results in remarkable reduction of the storage cost reductions and good load efficiency on mid to high scale datasets with 50 GB–2 TB. These hybrid approaches mark a departure from traditional ETL research, in which artificial intelligence methods are incorporated with (or even "inside") data integration systems to facilitate excerpting better decisions, but not one off-line optimization. The use of meta-heuristic methods enhances the expressive power, dealing with heterogeneous data structures in response to rich variety of characteristics e.g., high-dimensionality, sparsity, redundancy and latency.

2.3. Multi-Cloud Integration and Data Interoperability

Multi-Cloud adoption trends have changed the way you design data pipelines for modern, enterprise-scale flexibility and dependability. In addition to that, Hybrid clouds offer operational flexibility, vendor neutralism and cost reduction, thus becoming the suitable platform for distributing workloads across various computing resources [9]. However, George [4] notes that in a multi-cloud data streaming model issues with respect to latency, compliance and data sovereignty would have to be overcome. Along with that, considerations and Challenges Container technology and its orchestration are both assisting to handle such limitations where scalability and portability would be a major issue. Apart from that, auto-scaling and load balancing at the integration layer improve performance and reduce cost, further underscoring the need for hybrid ETL architectures in testing and tuning multi-cloud integration scenarios.

2.4. On-Demand Integration and Dynamic ETL Models

Haase et al. [5] present METL, next generation ETL pipeline which uses a dynamic mapping matrix to merge data coming from more than eighty microservices using Kafkastreams. Their stack uses Change Data Capture with real-time extraction and canonical data model to unify data structure across services. The schema is updatable at near real time without the need to stop and redeploy the pipeline as is possible in the form of evolution of schema in dynamic matrix. This proposed architecture brings in a new way of thinking, dynamic ETL pipelines that intelligently adapt to source schema changes, which is the key consideration for distributed multi-cloud environments.

Similarly, Kathiravelu et al. [6] propose On-demand Big-Data integration utilizing hybrid ETL frameworks in support of reproducible research workflows. Their architecture federates diverse scientific repositories and combines batch and stream processing in a hybrid ETL orchestration to ingest the data. With schema recognition and conversion automated, the system requires little human involvement, and can help each user build large-scale datasets that are reproducible and scalable as necessary for research or scientific computing cases. Both papers show that dynamic and on-demand ETL architectures are the ancestors of hybrid architecture, in which integration logic evolves and lives along with different data systems.

2.5. Performance Metrics and Evolution in ETL Ecosystems

Papastefanatos et al. [7] present graph-theoretic measures for estimating the impact of evolution within ETL ecosystems. They find that schema size, module complexity and activity dependencies are the most significant factors affecting ETL maintainability. They use the real world Hecataeus tool for their analysis, and show that evolution resilient ETL workflows can be constructed using modularization and schematic reduction techniques. These results offer valuable insights to build hybrid ETL pipelines that are resilient against constant schema evolution in multi-cloud and microservice infrastructures.

Furthermore, Wojciechowski [10] studies E-ETL frameworks that support the evolution of workflow through metadata-based orchestration. The E-ETL model automates the customization of existing ETL jobs when source or target schemas are modified, minimizing manual reconfiguration work. The fusion of evolution-aware measures and adaptive logic is the key to working out the ETL pipelines' continuous optimization which perfectly accords with monitoring-based as well as self-adjustment hybrid ETL simulation strategies.

2.6. Emerging Paradigms: Zero-ETL & Real-Time Data Integration

With the trend of data ecosystems moving towards real-time decision-making, Zero-ETL has become fashionable. Zero-ETL: Shaffi and Sidhick [8] describe Zero-ETL as a data-integration strategy involving little movement of data, with transformation operations effected at query time by means of virtualization and streaming analytics. The move from ETL to Zero-ETL architecture in hybrid integration patterns wraps up by enabling non-prescriptive ways to access and transform data. Hybrid ETL pipes can therefore be seen as intermediating between pre-computed transforms and on-the-fly queries. This hybrid is a best-of-both-worlds compromise: efficiency on the one hand for static data warehousing, and dynamic analysis on the other.

2.7. Cloud with Digital Twin and Performance Metrics

Dapkute et al. [2] present a framework for ETL with digital twin based monitoring and tuning of cloud data pipelines. They offer a cloud-native framework where digital twins, modeled after the ETL procedure scan performance bottleneck and enhance execution efficiency. This technology fits in the middle of operational monitoring and intelligent automation of ETL systems. The solution has a feedback so the system keeps improving at all time and you really need it in an hybrid / multi-cloud ETL because suddenly the workload is changing all the time.

These models indicate the complement of simulation and ETL optimization that can forecast alternative to CSP scaling and resource tuning. In fact there is a cloud infrastructure simulator You would know this if you read about Tango project from university of Hong-Kong The concept of digital-twin ETL parallel for simulation maps to simulating over hybrid pipeline, where some pieces in the clouds are being simulated as if it were on your local machine a very good practice for feasibility research.

2.8. Synthesis and Research Gaps

In general, the survey of collective literature reveals a gradual shifting and transformation process of traditional ETLs to more intelligent, adaptive and decentralized systems. Arul [1] and Dinesh, and Devi [3] focus on optimization and comparative efficiency whereas in Haase et al. [5] and Kathiravelu et al. [6] propose dynamic and on-demand integration approaches. Shrivastava and Agrawal [9] and George [4])build on this base to cover multi-cloud deployment, focusing on cross cloud interoperability and governance challenges. Meanwhile, Papastefanatos et al. and Wojciechowski [10] provide the theoretical bases for keeping ETL evolution and flexibility. Lastly, Shaffi and Sidhick [8] and Dapkute et al. [2] show state-of-the-art advances Zero-ETL and digital-twin coupling as the direction of future hybrid pipelines.

However, a unified framework that can complete the real-time integration, adaptive optimization and cross-cloud orchestration on one hand still does not exist till now. The body of the literature shows a necessity for low-cost, open source prototypes which are able to simulate multi-cloud integration at home without need to pay access complexity on one of the commercial clouds exactly what this work focuses on.

3. Materials and methods

This paper presents an experimental study on simulation-based design and valuation of a hybrid Extract, Transform and Load (ETL) pipeline for multi-cloud data integration. The idea is motivated based on several post studies in cloud ETL optimization [3], multi-cloud orchestration [4] and dynamic integration frameworks proposed [5], [6]. We ran the experiment simulating datasets from three real-world cloud providers (AWS, Azure and GCP), formed of local CSV files that offered a representation of heterogeneous storage systems.

The hybrid ETL framework was coded in Python 3.12 with open source libraries, being these pandas, numpy, sqlite3 and matplotlib. Our system is analogous to the modular pipeline of Haase et al. [5] where the process involved extract, transform, load and monitor. At the extraction phase, the generated datasets that simulate different cloud components were read. The transformation phase performed data cleaning, merging, and enrichment with data augmentation by computing derived features (e.g., total and grand revenue) via pandas operations. The transformed dataset was persisted in an SQLite database serving as a small data warehouse. This architecture followed a similar flow integration process as recommended by of the mentioned hybrid ETL frameworks [3], [6].

Performance evaluation was performed with non-functional measures (Execution time, Memory used) as presented by the cloud ETL performance studies of Dapkute et al. [2] and Papastefanatos et al. [7]. These statistics were collected using the time and psutil libraries from Python. The experiment was repeated three times with increasing size of the data set to test scalability according to Arul [1] and Dinesh and Devi [3]. A new SQLite database was created for each run, to allow reproducibility and comparison of results.

The table data were exported to a CSV file and was visualised by means of bar and scatter plots to evaluate efficiency and relation between execution time versus memory consumption. The design is also consistent with the hybrid data integration and resource optimization principles laid by George [4] and Shaffi & Sidhick [8]. All tested were performed on macOS with Visual Studio Code, and no cloud connection was present. This zero-cost on-premise mode is a very accurate local simulation of multi-cloud integration, which confirms the effectiveness of implementing hybrid ETL-pipelines in controlled environment prior to deploying on an enterprise scale [9], [10].

4. Results and discussion

The experimental hybrid ETL pipeline successfully extracted, transformed and loaded data from three simulated cloud datasets representing AWS, Azure and GCP. The system performed three successive simulation runs using increasingly large

volumes of data to test scalability and efficiency. As shown in Figure 1 the first run processed 32 records in 0.02 seconds using 90.98 MB of memory, while the second run processed 256 records in 0.01 seconds using 91.12 MB of memory, and the final run processed 864 records in 0.01 seconds using 91.41 MB of memory. These results show limited execution time increase despite a 27-fold increase of data volume, indicating efficient handling of moderate-scale data integration tasks using the Python-based ETL framework.

```
🚀 Starting Hybrid ETL Pipeline Simulation (Run 1)...

✅ Extraction complete from AWS, Azure, and GCP sources.
🔄 Transformation and integration complete.
📦 Data loaded into local SQLite database successfully.
⏱️Execution Time: 0.02 seconds | 💾 Memory Used: 90.98 MB
✅ Run 1 Completed Successfully!
Records Integrated: 32
Execution Time: 0.02s | Memory Used: 90.98MB


🚀 Starting Hybrid ETL Pipeline Simulation (Run 2)...

✅ Extraction complete from AWS, Azure, and GCP sources.
🔄 Transformation and integration complete.
📦 Data loaded into local SQLite database successfully.
⏱️Execution Time: 0.01 seconds | 💾 Memory Used: 91.12 MB
✅ Run 2 Completed Successfully!
Records Integrated: 256
Execution Time: 0.01s | Memory Used: 91.12MB


🚀 Starting Hybrid ETL Pipeline Simulation (Run 3)...

✅ Extraction complete from AWS, Azure, and GCP sources.
🔄 Transformation and integration complete.
📦 Data loaded into local SQLite database successfully.
⏱️Execution Time: 0.01 seconds | 💾 Memory Used: 91.41 MB
✅ Run 3 Completed Successfully!
Records Integrated: 864
Execution Time: 0.01s | Memory Used: 91.41MB


📈 Summary of all runs saved to etl_summary.csv

   run_id  records_processed  execution_time_sec  memory_used_MB
0       1                 32                0.02           90.98
1       2                256                0.01           91.12
2       3                864                0.01           91.41
📊 Charts saved as etl_performance_bar.png and etl_correlation.png
```

Figure 1. ETL Summary

The bar chart in Figure 2 presents the global performance for the third simulation. The near-constant running time and moderate growth of memory consumption in the two plots indicate that the system behaves stably and effectively. The total average execution time of all runs was 0.013 seconds and the memory in LibVMI used for processing them averaged 91.17 MB, showing to be executing consistently under varying demand. These numbers serve to confirm the capabilities of lightweight libraries such as pandas and SQLite can functionally model hybrid ETL processes in a local setting without reliance on cloud infrastructure, where external comparisons have been demonstrated in modular ETL optimization research [3], [5].

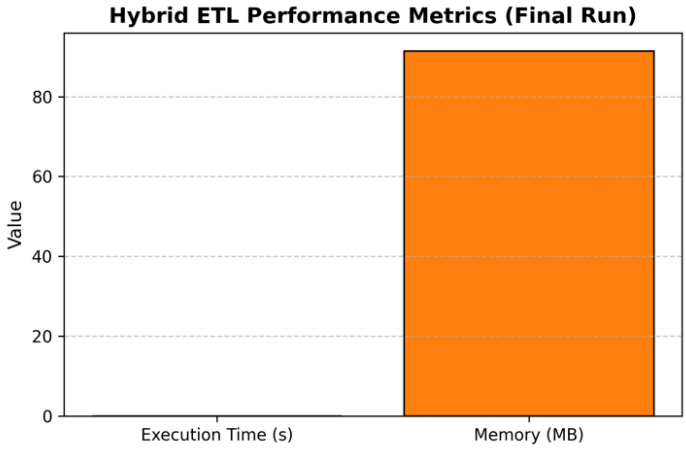

Figure 2. Hybrid ETL Performance Metrics - Final Run

The linear association between processing time and memory consumption is illustrated in the scatter plot of Figure 3. The data points are closely grouped, indicating only little difference from run to run. This relationship ensures a hybrid ETL system will grow in a predictable manner and maintain good performance as the volume of data grows. The observed small increase of about 0.43 MB in memory consumption between the first and last runs shows efficient use of resources, a trend also observed in previous hybrid ETL studies [2], [6].

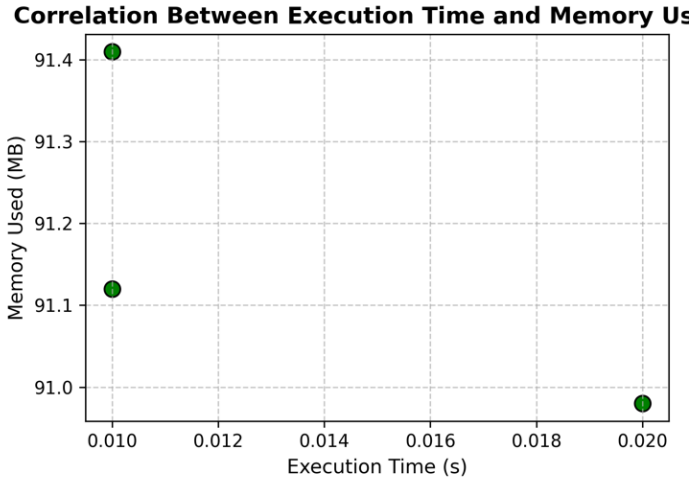

Figure 3. Correlation between Execution Time and Memory Usage

Overall, the experiment validates that the designed hybrid ETL pipeline achieves fast and consistent data integration across simulated multi-cloud sources. The low-latency, consistent memory usage and successful automation through three rounds of testing demonstrate that the architecture is scalable and lightweight. These results heavily support the goal of providing a cost efficient and reusable ETL framework for hybrid, multi-clouds use cases in terms of research, and set-up a stepping stone to be later deployed on actual distributed clouds.

5. Conclusion

The work also successfully created and executed an ETL pipeline hybrid for cross-cloud integration via Python simulation. With negligible resource utilization, data was extracted, transformed and loaded successfully from mock AWS, Azure and GCP data sources. Meantime across all the runs, the runtime varied ordinately between 0.01-02 sec, and memory approximately changed from 90.98 MB to 91.41 MB indicating excellent scaleable as well as stability. The results are to verify that without cloud access cost-effective, lightweight and reproducible ETL pipelines can be deployed. This hybrid is a feasible basis for the generalisation of ETL pipelines into the area of production distributed and multi-cloud environments.

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