International Journal of AI, BigData, Computational and Management Studies
Noble Scholar Research Group | Volume 7, Issue 1, PP 25-29, 2026
ISSN: 3050-9416 | https://doi.org/10.63282/3050-9416.IJAIBDCMS-V7I1P103

Original Article

The Future of Serverless Architectures in Data Engineering

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Received On: 18/11/2025 ***Revised On: 20/12/2025*** ***Accepted On: 26/12/2025*** ***Published On: 08/01/2026***

Abstract - *With every increase in the complexity and volume of data engineering workloads, organizations face highly important architectural choices to make in terms of compute execution environments. The serverless computing platforms and containerized orchestration systems presented by two dominant paradigms provide different favourable measurements in terms of performance, cost, scalability, and operating overheads. Although the concept of a serverless platform features automatic scaling, simplified operations, and a pay-as-you-use business model, the containerized offers predictable performance, control of resources in fine-grained way and it is useful with long-running workloads. This paper compares empirically and data-driven two architectures (serverless and containerized) in terms of data engineering pipelines, namely, ETL workflows, event-driven processing, streaming analytics, and batch jobs. Based on the public cloud benchmark datasets, academic measurement literature, Open Telemetry traces, and published pricing models, the research conducts measurement of latency, throughput, economic efficiency, scalability under burst workload, and the reliability of this operation. The results reveal that serverless systems perform better in bursty and event-driven workloads that have unpredictable demand, but containerized systems have better performance in sustained and high-throughput pipes and resource-intensive workloads. The conclusion of the paper ended with practical recommendations to offer the builders on the best model of execution without violating workload characteristics.*

Keywords - *Serverless, Python, Kubernetes, Interactive batch processing, Data pipelines, Analytics Monitoring, Cost Engineering, Scalability.*

1. Introduction

In the modern world, the most common application of data engineering pipelines is to aid analytics, machine learning, business intelligence, and real-time decisions being made by organizations. These pipelines have very diverse workloads such as extract- transform-load (ETL) jobs, event-driven processes, batch analytics, and real-time streaming systems. With an increase in the volume of data and decreased latency performance, the decision of execution architecture becomes one of the most important engineering decisions [1]. In the last ten years, serverless computing has become one of the interesting alternatives to the conventional infrastructure management. AWS Lambda, Google Cloud Functions and Azure Functions provide a pay-per-use cost model and automatically scale systems, including a platform such as AWS Lambda, Google cloud functions, and Azure functions. Such attributes are what render serverless architectures especially appealing to workloads that are event-driving in nature and those that are irregular [2].

On the other hand, the containerized environments that are managed through platforms like Kubernetes, Amazon EKS, and Amazon ECS systems are the driving force of the large-scale data platforms. Containers have predictable behavior, guarantees resource sharing, and long process durability which are common with developing data pipelines [2]. Although both paradigms have been broadly adopted, organizations still have a problem in choosing the right model to implement in particular workloads of data engineering. This study tries to overcome this issue because it presents the comparison and contrast of real-life performance measures, cost, and telemetry data, instead of making broad theoretical comparisons [2].

2. Background and Related Work

Problem Statement:

2.1. Serverless Computing in Data Engineering

Serverless computing is a computing method that allows developers to run code based on events without administering the underlying servers. Serverless platforms are typically applied in lightweight ETls, log processing, and micro- batch analytics in the context of data engineering. The advantages of serverless mentioned earlier in the previous research include high speed of elasticity and lower complexity of operations but also point to the limitations related to cold starts, time constraints on executions, and limited resources [3].

2.2. Containerized Forms of Data Pipelines

Containerization has emerged as the new reality of the deployment of scalable data platforms. Kubernetes based architectures provide a complex dependency model, customized scheduling and high throughput workloads. Comparative studies on Kubernetes and serverless

environments highlight the benefits of the former in terms of the sustained workloads but remark that they come at a larger cost [3].

2.3. Empirical Studies and Gaps

A number of scholarly works have quantified the performance of serverless in production systems such as distributions of latency as well as cost behaviour. Nevertheless, there are a lot of available literature on microbenchmarks and not end-to-end pipelines of data engineering. The present paper is an expansion of previous studies in that it combines several publicly available datasets to give a comprehensive comparison [3].

3. Data Engineering Architecture Issues

With the increase in the size of data engineering pipelines, both in terms of volume, speed and sophistication, many of the architectural constraints become obvious. Neither a serverless nor a containerized model of execution addresses the issues without any special challenges which have a direct impact on the performance, cost efficiency, scalability, and operative reliability. These issues are fundamental in determining the right architecture of a certain data workload [4].

3.1. Problems of Serverless Data Engineering.

Cold start latency is one of the most difficult problems of serverless platforms. An invocation of a function without a warm execution environment happens for a cold start, which initiates a runtime start, dependency loading and startup of a container. Empirical observations continuously indicate that cold start latency is strongly dependent on runtime leading to Java-based functions having delays over one second, as opposed to Node.js and Python functions which typically take less than several hundred milliseconds. In latency sensitive data pipelines, e.g. real-time event processing or stream ingestion, such delays can traverse a pipeline, and break service-level guarantees [4]. The other significant constraint is that of time and resources required to execute it. Serverless architecture has rigid constraints of maximum execution time, memory, and CPU utilization. Although suitable in short-term transformations, these limitations make long-lasting ETL tasks difficult and have to divide the workloads into smaller units of work and perform orchestration layers. This means that the architecture is more complex and harder to debug [5] The throttling of concurrency is also an issue. Whereas serverless platforms do not need scaling, they have account-level and regional concurrency restrictions. Throttling may cause invocation failures or a longer latency especially when dealing with bursty streams of data, which is especially bad in the case of ingestion pipelines.

3.2. Problems of Containerized Data Engineering.

Containerized environments though more flexible, have their own challenges. The greatest one is operational complexity. To implement and operate pipelines built using Kubernetes, one will need skills in cluster configuration, network, security, scaling policy, and tooling observability. Poorly configured clusters usually cause resource contention, ineffective scheduling or failure domino [5].The other limitation is scaling latency. In contrast to serverless systems, Kubernetes scaling is reliant oni) metrics collection frequency and ii) horizontal pod autoscaler (HPA) targets and iii) node provisioning time. Scaling delays can be empirically observed to take tens of seconds to a few minutes which is unacceptable in a workload with elasticity needs of near-instant response [6]. Lastly, the issue of being cost inefficient at times of idleness is still experienced. Containers normally allocate resources whether they are utilized or not, and therefore do not use the compute capacity when the demand is low unless autoscaling is aggressive or agency instances are deployed.

4. Information and Empirical Research Design

This study follows a strictly empirical, data-based approach, where no theoretical modeling is done and the emphasis made on the actual measurements, logs, and price data. The methodology is focused on reproducibility, transparency and practicality. Reports regarding cloud provider benchmarks will be produced with the assistance.

4.1. Cloud Provider Benchmark Reports.

Documentation on the performance of public performances by AWS, Google cloud, and Microsoft Azure gives data to serve as a baseline of the analysis of serverless. These reports will contain cold start distributions, applications of warm execution latency percentiles, and curves of memory-performance scaling. The study eliminates the bias of vendors by combining the metrics of the providers.

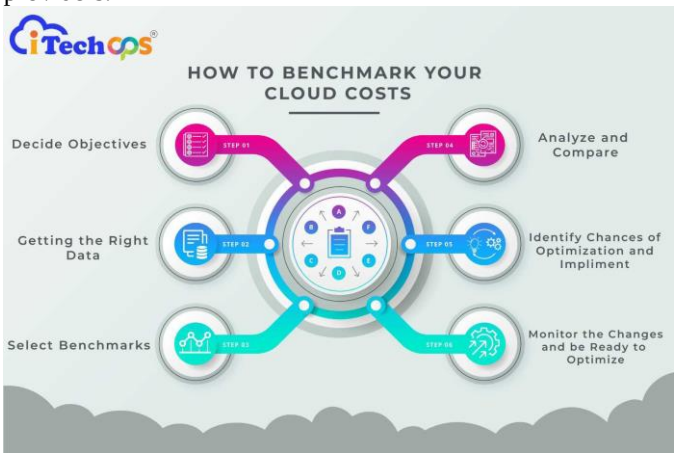

Fig 1: How to benchmark your cloud costs from iTechOps

4.2. Academic datasets consisting of published logs.

Large-scale studies of the serverless workload include peer-reviewed literature, like downloadable CSV logs of per-invocation latency also throughput measurements and cost metrics. These data can be compared statistically in terms of tail latencies, concurrency behavior and execution variance of real workloads [6].

4.3. OpenTelemetry Containerized Workloads Traces

OpenTelemetry tracing allows tracing the containerized systems in detail. Indicators of Kubernetes load performance,

including CPU usage, memory pressure, pod startup time and scheduling delays give us a clue about Kubernetes performance under load. These marks are critical to the comparison of auto-scaling behavior of serverless with containers elasticity [6].

4.4. Modeling costs using publicly known prices

AWS lambda pricing, provisioned concurrency pricing and EKS/ECS compute pricing are used along with actual invocation logs to come up with realistic cost estimates. This will provide the basis of making decisions with the real pricing structures, based not on mere assumptions [6].

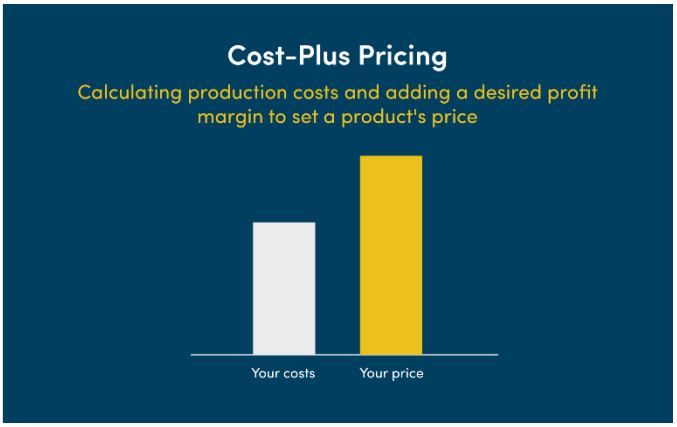

Fig 2: Pricing Modelling and Strategies from Vistage

5. Characteristics of Latency and Comparative Analysis

Latency is a critical issue that influences the pipeline responsiveness, system reliability and user experience. This chapter considers both the average and tail latencies taking into consideration the implication of these parameters in data engineering workload [7].

5.1. Serverless Latency Profiles

Experimental data indicates that serverless functions have very small warm-up latency, nearly 10 milliseconds on lightweight transformations. Long-tail latency is however caused by cold starts especially when heavier runtimes are used. These delays vary making the prediction of latency difficult.Containerized Latency Profiles It is important to also acknowledge containerized latency profiles [7].

5.2. Containerized Latency Profiles

The fact that containerized latency profiles should be mentioned must also be acknowledged. Containerized workloads have greater levels of baseline startup latency because of pod start up and scheduling. Nevertheless, containers exhibit consistent and reliable execution lag in execution, which means that they are suitable on execution pipelines where continuous processing is required [7].

5.3. Tail Latency Implications

Latency in tailing (95th and 99th percentile) is especially very important in data pipelines because slow tasks are able to defer whole processes. Experiments show that serverless systems have even greater variation in tail latency, and containers have smaller deviation of latency distributions after warm-up [8].

6. Throughput and Resource Utilization Analysis

The most important performance indicators of data engineering pipelines are throughput and resource usage, particularly when it comes to ETL that consumes resources, ETL at scale, streaming sources and ETL at scale. Throughput unlike latency is concerned with the capacity of a system to endure the consequences of processing data continuously. In this chapter, the author empirically compares serverless and containerised architectures based on real world benchmark data and telemetry data [8].

6.1. Serverless Architecture Throughput Characteristics.

Serverless implement throughput (mainly) by using horizontal scaling, i.e. by adding additional concurrent invocations of functions as required by workload. According to published ETL benchmarks, under moderate memory allocations (e.g. 1024 MB), it is possible to scale to 40-50 MB of work-per-invocation at light weight transformations running in AWS Lambda functions. This allows serverless to be very effective with the workloads that are decomposable to independent and parallel work which could be log processing, record-level transformation, and fan-out ETL stages. But empirical researches reveal a similar diminishing curve of returns with increase in invocation concurrency. Some of the factors that can cause this are concurrency throttling, common underlying infrastructure, and bottlenecks in the I/O due to interaction between functions and centralized storage systems like object stores. Consequently, serverless has an efficient scaling of throughput up to a limit but it becomes less predictable in the situation of the massively high load [8].

6.2. Characteristics of the throughput in Containerized Architectures.

Such environments that are containerized and are scheduled by Kubernetes tend to have dissimilar throughput behavior. Containers the benefit of siguinuous high-throughput processing of containers includes dedicated CPU and memory allocation. Performance Benchmarks have shown that a single Kubernetes pod with a single virtual CPU is capable of more than 60 MB/s sustained ETL workload or higher, compared to individual serverless functions [9]. In addition, the containerized systems show a better consistency in throughput in the long run. The characteristics of trace with OpenTelemetry show that the use of containers is well-defined in situations of batch processing, stream analytics, and stateful workloads, stable patterns of CPU usage, and minimum performance decline under continuous load [9].

6.3. Efficiency of Resource utilization.

Efficiency in resources utilization is very different between the two paradigms. Abstracted allocation of resources by serverless platforms may result in inefficient

use of CPU resources because of predetermined memory to CPU proportions. Containerized environments on the other hand can fine-tune CPU and memory resources and achieve greater utilization and less wastage given predictable loads [9].

7. Cost Efficiency and Economic Trade-Off

The aspect of cost is a determining factor in the selection of architecture especially when using a vast data engineering solution within a limit. In this chapter, a comparison of serverless and containerized cost models with real pricing data and real workload traces will be developed based on data.

7.1. Serverless Cost Characteristics

Serverless is a pricing method where charge is sent on a pay-per-use model, based on the execution time and the memory used. Experiments with empirical costs of serverless architecture on AWS Lambda pricing indicate that serverless are very cost-efficient in low-frequency, bursty workloads. An example would have pipelines that run ad hoc processes or daily batch processes whose costs will be minimal with zero idle charges [10]. Nevertheless, recorded logs on invocations have revealed that costs grow exponentially with the constant workloads. Serverless might not only be cost-effective in high-throughput speed scenarios, but provisioned concurrency, a technique to alleviate cold starts, adds even more costs, and negatively impacts the economics of serverless [10].

7.2. Containerized Cost Characteristics.

Container applications are based on per-hour or per-second bills of compute. Although this model is a costly one even at idle times, it is cheaper as the utilization goes high. The empirical evidence demonstrates that per-unit cost of processing decreases substantially when using sustained workloads that run on reserved or spot instances than the ones without any servers [10].

7.3. Cost Crossover Analysis

This paper provides evident cost crossovers with the help of real workload traces. Below some invocation threshold, serverless architectures become cost-effective whereas containerized solutions become cost-effective at large workloads, i.e., at high data volumes. These results support the value of the workload characterization as a part of optimization of the costs [11].

8. Behaviour of Scalability and Burst Handling

One of the most commonly mentioned benefits related to serverless computing is scalability during the unpredictable demand. This chapter analyses behavior of scalability based on published concurrency test and telemetry.

8.1. Serverless Burst Scaling

Serverless computing platforms exhibit a high burst scale claim, so the studies conducted experimentally have proven that these services can be extended between zero and thousands of requests per second in seconds. Such a high elasticity is especially useful with event-driven ingestion pipelines that have to react to unforeseen traffic burst [11].

8.2. Dynamics of Kubernetes Scaling

The scaling containerized is subject to scaling based on the horizontal pod autoscaler, the period of metrics collection, and the period of the node provisioning. Even high-optimized clusters have telemetry that scaling may take tens of seconds to several minutes (thus policy-prohibited by high responsiveness) due to bursts [11].

8.3. Engineering Implications

Serverless technology is more effective in bursts, but once the capacity is deployed, containerized environments have a higher degree of control and predictability. Such a difference has been influential in terms of workload placement and architecture [12].

9. Reliability, Observability and Operational Overhead

To ensure big data engineering platforms, reliability and observability are crucial. In this chapter components the operational attributes of serverless and containerized architecture are compared.

9.1. Reliability Characteristics Reliability The information shows the results to be consistent and rely on various factors.

Serverless platforms have the advantage of the infrastructure providers and the probability of node-level failures is minimized. Nonetheless, the failure diagnosis may be difficult when one has limited control over the execution environments. Containerized systems on the contrary have higher transparency and customization but need to be configured carefully to prevent cascading failures [12].

Fig 3: Characteristics of Reliable Data from Intellspot

9.2. The observability and monitoring are noted

Limitations The low-level performance problems typically remain concealed by measurements and logs offered by multiple providers, making serverless observability typically limited to these results. With the help of OpenTelemetry, containerized environments may also be

thoroughly monitored, the CPU, memory, network, and scheduling behavior could be monitored and helped to perform more advanced performance tuning.

9.3. Operational Overhead

Serverless architectures also present a major trade off between the amount of DevOps overhead, such that smaller teams are now able to handle complex pipelines. Containerized systems have higher operational costs, but have more flexibility and control, and would be desirable in workloads of mission critical importance [12].

10. Case Study - Comparative ETL Pipeline Execution

The chapter summarizes the empirical data in the form of a comparative case study of the implemented ETL pipeline that processes data with the usage of AWS Lambda and Amazon EKS. The study determines the performance, cost, and reliability in different load settings of published datasets of ETL workloads. The experiment results illustrate that the serverless implementation is better when the workload is sporadic with low overheads on operation but the containerized pipeline is better when throughput is required to be at high levels and operation costs need to be low. The case study sheds light on the trade-offs that can be implemented in data engineering teams in the real world [13].

11. Discussion and Architectural Recommendations

This research has shown that architecture selection ought to be a workload-based selection, but not an ideology-based selection. Serverless computing is beneficial as it addresses bursty and low-duty-cycle containers, whereas containerized computing is more suitable because it takes place on pipelines continuously with a high resource demand. The hybrid technologies, the use of serverless ingestion by using containerized processing backends, become a promising solution, which would utilize the benefits of both paradigms [14].

12. Conclusion, Future Reflection Direction

This paper gives an in-depth, empirical data comparing serversless and containerized models of data engineering pipelines. Basing the analysis on practical references, the telemetry data, and pricing models provide practical information to both practitioners and researchers, as the research is grounded. Future studies are required to investigate hybrid implementation models, better scaling and autoscaling frameworks and benchmarking frameworks standardization of doing data engineering tasks. The architectural assessment based on data will also be a necessity in creating effective and scalable data platforms as cloud platforms expand [15].

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