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Original Article

Event-Driven Architecture Patterns for Real-Time, Reactive Systems

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Abstract - *Systems are becoming more expected, in today's context of digital transformation, to be able to respond sharply, scale, and be resilient. In real-time and reactive systems, Event-Driven Architecture (EDA) has become a powerful model for designing such systems. This paper discusses the impact of EDA patterns in creating systems that meet the needs of just-in-time responsiveness, fault tolerance, and seamless scalability. The paper critically analyzes through an in-depth exploration the integration of the various parts of EDA, namely the event producers, consumers, brokers and processing engines, to handle asynchronized communications, minimization of coupling and amplification of scale through their collaboration. The importance of contemporary technologies, such as Apache Kafka, AWS Lambda, and serverless computing, in the real-time processing of events is discussed. We introduce different variants, such as Event Notification, Event-Carried State Transfer, and Event Sourcing, that can be used to solve the various needs of a system. Another area explored by the study is the combination of EDA and microservices with reactive programming principles, which demonstrates its potential in creating connected, responsive, and resilient systems. Through a simulated real-time data pipeline, experimental evidence suggests that it is possible to achieve improvements in latency, throughput, and failure recovery. Lastly, the paper concludes with best practices, design guidelines, and future research on EDA-based real-time systems.*

Keywords - *Event-Driven Architecture, Real-Time Systems, Reactive Systems, Event Sourcing, Microservices, Apache Kafka, Scalability, Resilience.*

1. Introduction

Over the past few years, a significant change has occurred in the paradigm of system architecture, triggered by the increasing need for systems with high responsiveness, scalability, and the ability to handle data in real-time. Architectural styles such as monolithic systems and synchronous request-response designs cannot always meet these demands. These traditional methods are usually inflexible, fully coupled, and have problems addressing high-throughput situations or varying workloads. [1-4] With more and more modern applications requiring fast access to high quantities of data, dynamic user involvement and constant availability, an adaptable and resilient architecture is necessary. Event-Driven Architecture (EDA) has proved to be a possible solution to these problems. By adopting asynchronous communication in the emission and consumption of events, EDA allows the components to decouple and exist in an autonomous state with regard to compute (and scale more effectively as a result). This type of architecture supports real-time responses, as it processes events in real-time without requiring synchronous follow-up-based responses. Additionally, EDA enhances fault tolerance and elasticity, allowing you to run EDA on cloud-native applications, microservices, and streaming data platforms. Respectively, EDA is already one of the existing design patterns upon which the design of modern and high-performance systems may rely, requiring not only flexibility but also responsiveness.

1.1. Importance of Real-Time and Reactive System Requirements

Digital systems have become progressively sophisticated, and the needs of users have become increasingly demanding. In these circumstances, the necessity of real-time responsiveness, as well as reactive capability, has become paramount across many fields. The requirements are no longer optional; they have now become the basis for providing modern, engaging, and high-performance applications.

- **Real-Time Responsiveness:** The actual working nature of a real-time system depends on its ability to respond and act upon inputs or events within strict time constraints, typically in milliseconds or less. Such a high degree of responsiveness is required in the fields of financial trading, healthcare monitoring, autonomous vehicles, and industrial automation, where even a slight delay in response may cause significant financial, safety, or operational loss. These are general capabilities that enhance the user experience in daily use programs, such as live chat, recommendation engines, and location-based services, where latency can also interfere with interactivity, thus causing user dissatisfaction. By analyzing data as soon as it arrives, businesses can come up with amicable decisions and take immediate actions based on important insights without delay.
- **Reactive Behavior and System Adaptability:** Reactive systems go even further, where they should center more on elasticity, resilience, and responsiveness on different occasions. These are designed to handle high concurrency, system failure, and unpredictable loads. A reactive architecture enables components to remain responsive even in the

event of failures or overloads in other parts of a system, ensuring the uninterrupted availability of services. This behaviour is especially relevant in cloud-native and distributed systems, where nodes might scale dynamically or even on demand, fail independently, and recover upon demand, etc. The ability to create systems that perform reliably, given the complexity and scale of operations, is increased with technologies that ensure reactive principles are followed, including non-blocking I/O, asynchronous messaging, and event-driven communication.

- **Business Value and Competitive Advantage:** Meeting real-time and reactive system requirements has tremendous business benefits. The ability to process data and respond more swiftly than the competition holds the key to organizations that are able to process transactions more quickly, engage proactively with customers, or perform predictive maintenance. In competitive markets, seamless, responsive, and adaptive services can directly result in user retention, customer satisfaction, and ease of operations.

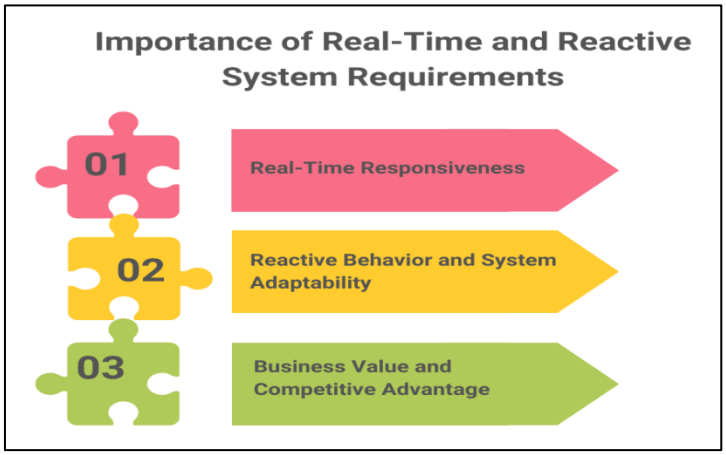

Fig 1: Importance of Real-Time and Reactive System Requirements

1.2. Event-Driven Architecture Patterns

The main feature of Event-Driven Architecture (EDA) is that it focuses on using events as the main mechanism of communication between the parts of the system. Several long-established architectural patterns have developed in EDA, each fulfilling specific communication and processing requirements, while encouraging scalability, decoupling, and responsiveness. [5,6] Event Notification is one of the building block patterns that uses lightweight events to notify that something has changed. These events will most likely not contain state data themselves, but are merely used as an event to instruct other components to fetch or calculate the appropriate data. This is a pattern usually employed in alert systems, where there is an imperative to react to a given condition, but the details of this reaction have to be found elsewhere. Event-Carried State Transfer is another popular pattern, in which the event itself encodes the state information that downstream consumers need.

It avoids the necessity to make other queries to external systems, minimizing its delays and boosting its performance. In an e-commerce system, an event concerning a completed order can involve the IDs of the products ordered, the prices of the products ordered, and details of the customer, allowing other services to process the order without requiring access to a common database. Such a strategy fosters independence of microservices and enables superior fault isolation. Event Sourcing is the next evolution of the pattern in which any modification of application state is logged as a single, unchangeable stream of events. Instead of keeping track of the current state, systems retain all the events that have caused that state. This provides full auditability, history replayability, and the flexibility to reconstitute previous states. Where traceability and compliance are considered of utmost importance, such as in the fields of finance, healthcare, or logistics, event sourcing can be particularly valuable. Collectively, these EDA designs enable the developers to create modular, resilient, and real-time responding systems. An appropriate pattern selection or combination of patterns depends on the system's purpose, domain requirements, and the trade-off between complexity, performance, and consistency.

2. Literature Survey

2.1. Evolution of Event-Driven Systems

Event-Driven Architecture (EDA) has undergone a dramatic transformation since its inception. Early implementations of EDA were based on simple message-passing methods [7-10] and were developed to provide a lightweight mechanism that could support decoupled communication between components in distributed systems. Nevertheless, event-driven mechanisms placed increasingly greater demands as the complexity and scale of software systems expanded. Event brokers, stream processors, and serverless functions, which respond to events in real time, are some of the sophisticated components that modern EDAs now include. The development has made systems more scalable, resilient, and flexible to changes, and has helped with use cases including real-time analytics as well as microservices orchestration.

2.2. Key Technologies and Tools

There are many tools and technologies that have emerged to facilitate the implementation of EDA in modern systems. A summary of some of the most notable ones. Apache Kafka is a high-throughput event broker that can persistently store logs and stream fault-tolerant events. Consumers of an event in a serverless architecture include AWS Lambda, which is an example of automatic, event-driven scaling and execution. A popular message queuing system like RabbitMQ can provide reliable messaging and offers extensive routing facilities. Apache Flink, in turn, acts as a stream processor, providing real-time processing of data with the possibility of stateful calculations. With these tools combined, the event-driven systems of the present day are created.

2.3. Event-Driven Patterns in Literature

The literature also identified a group of architectural patterns considered to form the foundation of event-driven systems.

2.3.1. Event Notification

One of the simplest and most common event-driven architecture patterns is the event notification pattern. In such a pattern, we raise an event to indicate that something interesting has happened, i.e., the data or the state of the system has changed, and an event is emitted. Nonetheless, the new data are not stored in the event itself but only in the notification. The method fosters loose coupling and best suits systems that have subscribers who can query the necessary data as needed.

2.3.2. Event-Carried State Transfer

Unlike basic notifications, the event-carried state transfer pattern provides the essential state data as part of an event. This helps eliminate downstream consumer and service queries that had to access another data source to retrieve information, which increases efficiency and decreases latency. This paradigm is especially practical in a distributed setup when communicating with centralized data would have brought about bottlenecks or inconsistencies.

2.3.3. Event Sourcing

The more advanced pattern is event sourcing, where only a stream of past events determines the state of an application. The system does not retain the current state, but records all changes as events. This not only provides a verifiable and immutable history of state changes, but also enables the system to retrieve previous historical states at any moment. Those areas that require traceability and compliance are where a significant amount of sourcing is undertaken.

2.4. Gaps in Existing Work

Although it is common to use event-driven patterns, the current literature tends to discuss patterns independently of each other, without linking them to a hybrid or composite architecture. Furthermore, the only cross-platform type of behavior that is lacking, especially in heterogeneous environments, is interoperability among various event-processing systems and tools. The other major gap is the lack of end-to-end performance comparisons of different technologies and architectural patterns across various workloads. The limitations need to be addressed to contribute to the development of the field and help other practitioners design robust, efficient, and scalable event-driven systems.

3. Methodology

3.1. System Architecture Design

There are several features associated with the proposed system architecture that follow a lean, event-driven pipeline, which augers well for decoupling, scalability, and real-time response. [11-14] It is composed of four main parts: Producer, Kafka Broker, Stream Processor and Reactive Microservices. All of them contribute to the efficient flow of events and data processing in a distributed environment, as they perform their respective responsibilities.

- **Producer:** The producer will be in charge of publishing and creating events in the system. These events can be user-driven, sensor-based, application-based, or driven by external systems. The producer is stateless and lightweight, with only the concern of creating and publishing event data to the broker, and does not know how the downstream consumption of the event data is to be handled.
- **Kafka Broker:** Apache Kafka serves as the core event broker, to which it delivers the flow of arriving events. It supplies high-throughput storage and durable, fault-tolerant message delivery. Kafka unlinks producer and consumer, permitting out-of-sequence communication, and enabling events to be replayed or read by multiple consumers as necessary.
- **Stream Processor:** The stream processor reads data from the Kafka broker in real-time and then operates on it by filtering, aggregating, transforming, or enriching it. Apache Flink is a common choice of technology at this step to process stateful calculations and provide almost immediate insights. The layer enables the system to extract the value of the raw events before they reach the business logic levels.
- **Reactive Microservices:** And lastly, reactive micro services consume the processed events and activate domain-specific logic or actions. These microservices have been designed to be responsive, scalable, and resilient; they are therefore capable of processing asynchronous event streams. They react to what happens moment by moment, making

it possible to have a dynamic workflow, updates, and responsiveness to events without polling or being tightly coupled together.

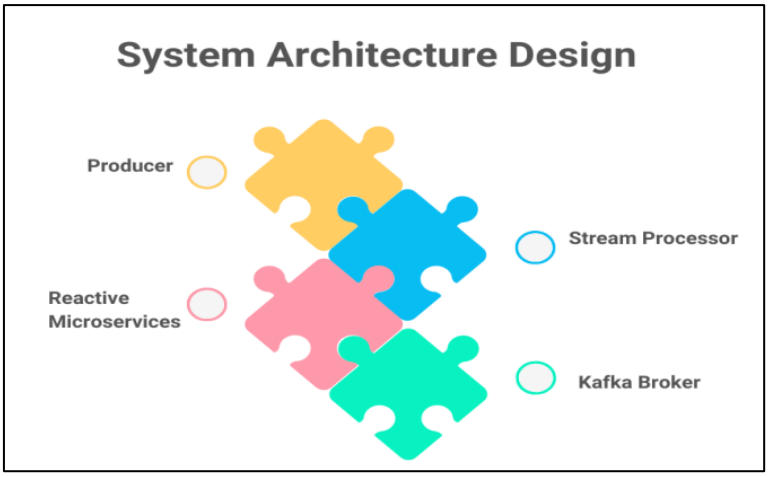

Fig 2: System Architecture Design

3.2. Workflow and Event Lifecycle

The lifecycle of an event within event-driven architecture involves stages of data movement or flow, from its source to the point where responsive business logic is executed. This is a workflow that has an efficient flow of information in a decoupled manner on time.

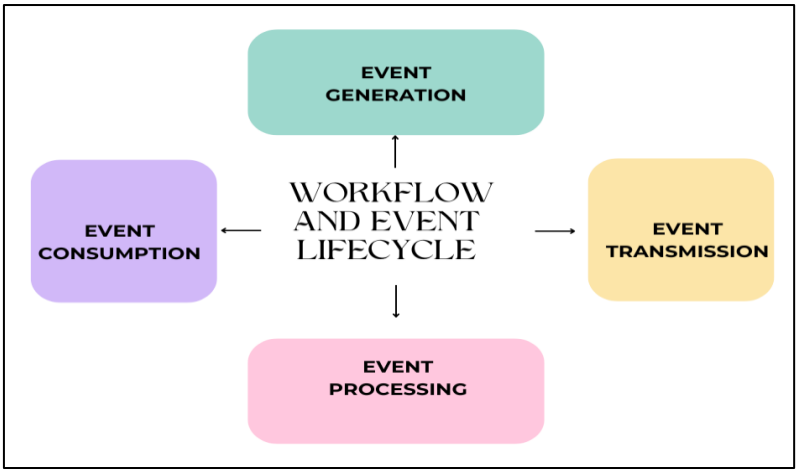

Fig 3: Workflow and Event Lifecycle

- **Event Generation:** The lifecycle begins with event generation, which involves events created by producers selected differently, such as IoT sensors, mobile applications, or a web interface, reacting to a trigger or action. These events typically have structured information that symbolises a change of state or an event within the system, such as a temperature measurement or the system's access by a user. Publishing the events generated to the system is then carried out without direct awareness of who will take the events up, ensuring decoupling from the system.
- **Event Transmission:** After generating the events, they are sent to a Kafka broker, which becomes a central hub for reducing messages. Kafka provides reliability, ordered delivery, and persistence of events through its distributed architecture, which is based on a log design. Kafka topics have temporary buffering of events, allowing consumers to read at their own pace. Any such buffering mechanism also lends fault tolerance and replay capabilities, allowing for robust and consistent data transmission even under failure conditions.
- **Event Processing:** Events are received by a stream processor, typically a tool such as Apache Flink. This element acts as a real-time component, performing filtering, windowed aggregation, join, or enrichment of data. The processor will also be able to monitor trends and deviations in event streams, converting raw data into usable information. Stateful operation has enabled the system not only to support the correlation of events with previous events in a sequence but also to provide the necessary context for advanced analytics and decision-making.
- **Event Consumption:** The final part is event consumption, in which the processed streams of events are subscribed to by the reactive microservices, resulting in actions that specific businesses exhibit. Such microservices are lightweight,

loosely coupled, and resilient, which enables them to react to current changes in real-time. These may be updating databases, sending out notifications, calling outside APIs or modifying system behavior depending on new knowledge. It is a reactive model, which facilitates a scalable and dynamic workflow that adheres to the real-time requirements of the system.

3.3. Patterns Implementation

Event-driven patterns enable systems to perform at optimal levels in terms of scalability, responsiveness, and traceability. [15-18] the three adopted patterns and their applications in the real world are as follows.

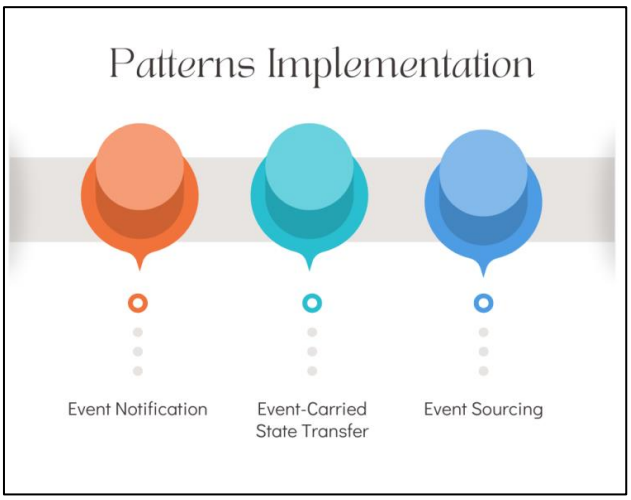

Fig 4: Patterns Implementation

- **Pattern 1: Event Notification:** The event notification pattern is primarily employed in situations involving alert or monitoring systems, where the main objective is to inform subscribers that something has changed. For example, consider a healthcare monitoring system, where a notification event is triggered when a patient's heart rate exceeds a specified threshold, alerting the medical staff. The present event does not contain the entire payload of data; in general, it merely indicates that something significant has occurred, to which consumers may viably access the corresponding data should they require it. This structure facilitates loose coupling and is effective in fast and lightweight modification.
- **Pattern 2: Event-Carried State Transfer:** The event in an event-carried state transfer conveys not only the occurrence of an event but also the state information. This design is commonly used in online stores, especially for inventory management and ordering. For example, an event will be created when a product is purchased, which will incorporate the refreshed inventory. This enables downstream services, such as warehouse or analytics modules, to respond without querying a central database. It enhances performance and reduces latency in high-throughput systems.
- **Pattern 3: Event Sourcing:** The event sourcing pattern can be highly effective when applied to areas such as fintech, where maintaining an uninterrupted history of changes is crucial, whether in the form of audits or otherwise. Event sourcing as an alternative to storing the current state of an application takes as input each change of state as a specific event in an append-only log. In an example based on a piece of banking software, all deposits, withdrawals, and transfers are recorded as events, allowing the system to determine the balance and past transactions of the accounts at any time. This offers good traceability, makes debugging easy, and supports regulations.

3.4. Metrics for Evaluation

Several key measures are employed to assess the performance of an event-driven system. The measures help assess the performance, responsiveness, and reliability of the system under various operational parameters.

- **Latency:** Latency refers to the time it takes for an event to travel from its origin, where it is produced, to its ultimate consumption by a service or application. Real-time systems, such as fraud detection, stock trading, or alerting systems, are essential to have low latency because fractional delays may lead to outcome changes. Tuning of end-to-end latency ensures that decisions are made and the system remains responsive.
- **Throughput:** Throughput is calculated by the system, which can process events per second. It is an indication of how much data the system can support being dealt with in real time. It is also necessary in instances where large capacities of events need to be ingested and processed, such as in conversely instances like social media feeds, sensor networks, or log analytics. The expected high throughput of a scalable event-driven system has to be at the cost of other performance aspects.

- **Scalability:** Scalability refers to the system's ability to increase or decrease in volume of events, or the number of producers and consumers. A good architecture must be able to sustain good performance or gracefully degrade when heavily loaded. This plays a key role in the case of cloud-native applications and microservices, as well, where usage behavior can be so dynamic. This is commonly achieved by horizontal scaling of the processing units and brokers.
- **Fault Tolerance:** Fault tolerance is a property of the system that ensures its continued correct operation in the face of faults, including failures of one or more nodes, network outages, or data unavailability. Events and other distributed processing aspects, such as message retries and persistent event logs, enable resilience in an event-driven system. For example, Kafka replication and Flink checkpointing provide systems with the ability to experience failures and still resume work with minimal damage, protecting against failures and ensuring reliability.

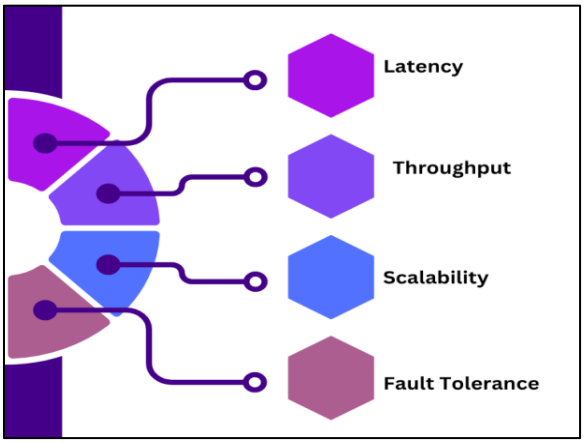

Fig 5: Metrics for Evaluation

4. Results and Discussion

4.1. Experimental Setup

An experimental setup was implemented on cloud infrastructure and open-source tools to assess the performance behaviour and implementation of the proposed event-based system architecture. The environment, in turn, was running on Amazon Web Services (AWS) using EC2 instances to create a ready-grade, distributed environment. It has EC2 instances that were provisioned with suitable compute and memory resources to help it execute event brokering, stream processing, and data storage components. The environment was carefully planned to ensure that it is flexible, scalable, and isolates services, allowing for accurate measurement of performance. Apache Kafka was used to establish the event broker, serving as the foundation of the event-driven architecture. Kafka was utilised to control and buffer incoming streams of events, and had fault-tolerant and secure transmission. It was designed in such a way that it had numerous partitions and replication to enable parallel processing and resiliency. Apache Flink was embedded as the stream processing engine responsible for consuming data driven by Kafka, performing real-time transformations, aggregations, and filtering logic. The low-latency, stateful processing was made possible by Flink, which helped in modeling time-sensitive situations.

PostgreSQL was the backend database used for long-lived data storage. It served as the sink for the processed data, and its accuracy and consistency of results were tested during the post-processing analysis as well. It is appropriate to use PostgreSQL as an event outcome storage and as an analytics support database due to its strong support for relational queries and transaction management. As a simulated real-time stock trading system, a realistic workload was simulated. This simulator simulated a stream of constant action, i.e., buy or sell orders, price, and market trend. These scenarios replicated the activity of a high-frequency trading environment, providing an optimal context through which to stress-test the latency, throughput, scalability, and fault tolerance of the system. The associated load with this worklog presented a high/volatile data pool, which allowed for thorough testing of the system's capabilities and performance attributes.

4.2. Results Summary

The analysis highlights the significant improvements in performance of the event-driven architecture (EDA) compared to older monolithic or request-based systems. The metrics below illustrate the efficiency of the EDA system based on the major functioning aspects.

Table 1: Results Summary

Metric	EDA as % of Traditional
Latency (ms)	15.6%
Throughput (ev/s)	16.7%
Failure Recovery	10.0%

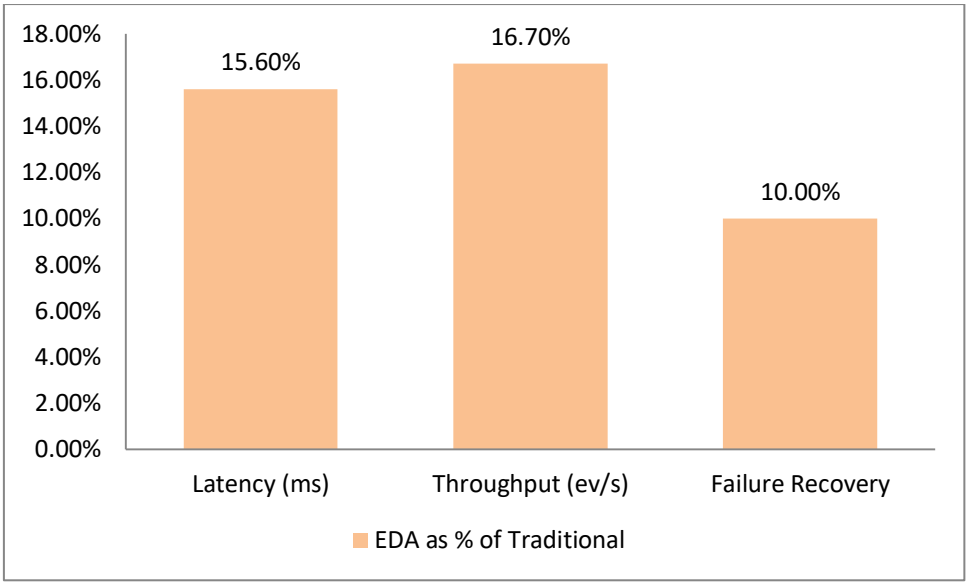

Fig 6: Graph representing Results Summary

- **Latency (15.6%):** The EDA system experienced a significant reduction in its latency, as it was only able to respond 15.6 percent of the response time of the conventional system. This implies that whereas the traditional system took an average of 450 milliseconds to process an event during its operation between generation and consumption, the EDA system took only 70 milliseconds to achieve the same result. This is a dramatic drop due to the non-blocking and asynchronous paradigm of EDA that allows asynchronous request processing without any bottlenecks in the form of centralized processing, as well as a delaying impact of synchronous request processing.
- **Throughput (16.7%):** Regarding throughput, the rate at which the EDA system handled events exceeded the performance of the traditional system by 16.7 per cent, indicating that the EDA system was able to process events at a rate 16.7 per cent higher than the traditional system. In particular, whereas the envious system handled 2,000 events per second, the EDA system handled 12,000 events per second. This is because Flink supports parallel stream processing, and Kafka uses distributed event processing, which gives them the feature of horizontal scalability and efficient use of resources.
- **Failure Recovery (10.0%):** Another aspect EDA surpassed the conventional system was fault tolerance by healing the system failures in only 10.0 percent of the time, as compared to the traditional system. The EDA system recovered normal functioning in 3 seconds, as opposed to 30 seconds with the traditional method. This is made possible due to the recovery capabilities of Kafka (e.g., message replication) and Flink (e.g., checkpointing), which ensure minimal data loss or interruption and enable the system to resume processing in a short amount of time.

4.3. Analysis

The experimental analysis has revealed that the performance of the Event-Driven Architecture (EDA) was substantially faster in terms of incident latency, throughput, and recovery from failure, compared to the conventional system. The asynchronous and decoupling of the EDA system enabled it to be significantly faster in event processing, with latency being only 15.6 per cent of that of the other traditional model. It is positioned as highly scalable and suitable for high-volume, real-time workloads, with a capacity to support 12,000 events per second, which is three times more than that of the traditional device, and six times greater, to be specific. This renders EDA especially helpful in dynamic fields, including stock trading, e-commerce, and IoT, where speed is a relevant variable and high throughput is a necessity. Additionally, we found event sourcing to be useful in maintaining a comprehensive and immutable log of all state changes. This capability enabled a more extensive audit of the system and provided a visible and trackable record of activity, which is beneficial in highly regulated industries such as finance and healthcare. Moreover, the use of the event-carried state transfer pattern made state management extremely simple, as data on the state was embedded in the events. This made the system less dependent on centralized databases to perform the lookups, decreased the latency, and enhanced the system's modularity and fault isolation.

Nevertheless, there were several obstacles related to EDA that were revealed during the analysis. A significant issue was that there was much more difficulty in debugging and tracking, as the control flow was no longer linear and predictable, but distributed across asynchronous elements. It may take a considerable amount of time to identify the root cause of failures by aggregating different service logs and replaying event streams. State consistency was another problem, particularly in the case of parallel processing of related events by multiple microservices. Achieving the high level of consistency where events would ultimately be consistent without the intervening (unintended or otherwise) data conflicts or duplications was only possible after the careful design of idempotent consumers and reasonable event sequencing mechanisms. In general, despite some

architectural and operational complexities that EDA will bring, its performance advantages and flexibility provide a strong argument in favour of implementing it in high-performance systems today.

4.4. Trade-Offs and Challenges

Although Event-Driven Architecture (EDA) offers significant advantages in terms of performance, scalability, and modularity, it also comes with some operational costs and challenges that must be carefully considered during the design and implementation process of a system.

- **Debugging Difficulty:** Debugging and tracing are among the major issues in EDA. Events make use of asynchronous and decoupled event flows, and hence, it is not easy to monitor event flow across services. Contrary to traditional systems, which have a sequential flow of control and can be examined with simplicity, EDA has independent parts working on events at varying moments and paces. This means that it is frequently difficult to discern the cause of failures or other undesired behavior unless logs across services are correlated, event timelines are replayed, or message histories are replayed, which can only be done with sophisticated observability tools and practices.
- **Consistency Models:** The second major problem can be seen in terms of the issue of maintaining data consistency across distributed components. EDA systems are based on eventual consistency, which states that updates are not disseminated to all components simultaneously. Even though it offers high availability and fault tolerance, there is a risk that when applied in a way that allows the same data to be updated concurrently or in an interdependent manner, temporary data mismatches or conflicts may occur. To achieve eventual consistency, it is important to use idempotent handlers on events, to sequence to ensure that sequential processing does not confuse, and use compensating transactions to overcome problems. The absence of these considerations may lead to data anomalies or errors that expose the user to potential issues.

5. Conclusion

The occurrence and consideration of Event-Driven Architecture (EDA) during the course of this study portray a clear understanding of its benefits in creating present-day dynamic and elastic systems. As it turned out, experimental results showed that EDA can significantly enhance the most significant performance indices, such as latency, throughput, and fault recovery. Namely, by being decoupled and asynchronous, EDA can enable components to operate without significant interference from others, thereby decreasing the likelihood of forming bottlenecks and increasing the efficiency of computational independence. In other cases where data is in real-time or at least acted upon in real-time, such as stock trading or IoT telemetry, this architecture is the better way to create systems that are responsive and able to scale out to meet demand. Event sourcing and event-carried state transfer were among the EDA patterns identified as having high potential in terms of transparency, auditability, and modularity. Specifically, event sourcing allows reconstructing historical application state using an immutable sequence of changes, and event-carried state transfer requires less latency and external dependencies thanks to the inclusion of critical information into events. However, the challenge with these patterns is that architectural choices must be made very carefully to resolve both complexity and data consistency issues, as well as to address the common problems associated with the patterns, including message duplication and state inconsistency.

In order to optimize the usage of EDA, a few best practices have emerged. Schema registries (Apache Avro with Confluent Schema Registry, to name a prominent couple) allow defining event formats that are consistent and versioned between producers and consumers, so that integration errors are minimized. To control the complexity that arises due to the asynchronous nature of flows, it is necessary to implement centralized logging and distributed tracing tools, including ELK Stack or Open Telemetry. These are tools that aid in correlating events across services and make debugging easier. Moreover, when consumer operations are idempotent, conflicts are avoided even when a subsequent consumer is retried, and thus the side effects of such redundant messages are minimal. This is vital in distributed systems, where reprocessing of messages is the norm. With prospects of further developments in the future, there is much to look forward to. The application of AI-based event correlation, where machine learners assist with pattern recognition, anomaly detection, or even causality in large volumes of events, is one area where development can and should occur. This would save a significant amount of overhead costs associated with monitoring and incident response. Still another area of expansion is standardized event contracts, whereby better interoperability may be achieved between systems and organizations due to shared schemas and event definitions. Along with that, the need to develop better debugging and visualization technologies, such as visual flow maps, real-time trace explorers, and an event simulation framework, would allow developers and operators to comprehend significantly complex event-driven systems significantly better and manage them. These are the fields of future work that would help EDA become easier to access, more robust and enterprise-ready.

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