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# Exploring the Distinctions in Characteristics, Framework Designs, and Toolsets of Big Data Systems

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**A B S T R A C T**

Big Data Analytics is gaining increased recognition as a valuable tool for analyzing vast amounts of data on demand. The most common Big Data processing frameworks include Apache Flink, Apache Hadoop, Apache Storm, and Apache Spark. Each of these frameworks varies in its approach and supporting architecture, yet all facilitate Big Data processing. Numerous studies have devoted time and effort to compare these Big Data frameworks by evaluating them based on specific Key Performance Indicators (KPIs). Upon comparing all four, Apache Spark emerged as the superior choice across all the identified KPIs, such as CPU usage, task performance, execution time, processing time, and scalability for non-real-time data, compared to Apache Storm and Apache Hadoop frameworks. However, Apache Flink excelled in stream processing regarding processing time, CPU usage, latency, throughput, execution time, task performance, scalability, and fault tolerance when compared to Apache Storm and Apache Spark frameworks. This paper summarizes previous work on Apache Flink by identifying a shared set of KPIs, including processing time, CPU usage, latency, throughput, execution time, sustainable concurrency level, task performance, scalability, and fault tolerance, and compares all Big Data frameworks along these KPIs through a literature review.

This comprehensive analysis of the widely-used Big Data frameworks – Apache Flink, Apache Hadoop, Apache Storm, and Apache Spark – aims to provide a clearer understanding of their respective strengths and weaknesses in various use cases. The identified KPIs serve as a guide for both researchers and practitioners when selecting the appropriate framework for their specific needs. To ensure a thorough comparison, we conducted an extensive literature review to gather relevant information and empirical data related to the KPIs. This review included various benchmarking studies, performance evaluations, and comparisons of the frameworks in different application scenarios. Our analysis revealed that, while Apache Spark outperforms Apache Storm and Apache Hadoop frameworks in non-real-time data processing, Apache Flink offers superior performance in stream processing tasks, exhibiting advantages in latency, throughput, and fault tolerance. Moreover, our findings suggest that each framework has unique features that make them suitable for particular applications. For instance, Apache Hadoop is ideal for batch processing tasks and large-scale data storage, while Apache Storm excels in real-time data processing, and Apache Spark provides a versatile platform for both batch and stream processing with a focus on in-memory data processing.

In conclusion, this paper offers valuable insights into the characteristics, performance, and applicability of popular Big Data frameworks, assisting stakeholders in making informed decisions when choosing the most suitable framework for their projects. Furthermore, our comparison lays the groundwork for future research on optimizing and enhancing these frameworks to better cater to the evolving needs of Big Data processing and analytics.

Keywords: Big Data Analytics, Apache Flink, Apache Hadoop, Apache Storm, Apache Spark, Key Performance Indicators, CPU Usage, Processing Time, Latency, Throughput, Fault Tolerance, Stream Processing, Batch Processing, Real-time Data Processing, In-memory Data Processing.

## 1. Introduction

The exponential growth of data due to technological advancements in recent years has brought Big Data to the forefront of research, generating a significant amount of attention [1], [2]. The volume of data has been growing rapidly, from a few bytes to zettabytes, with social media as the primary source of structured and non-structured data. This has led to a significant increase in data size, with Twitter having thousands of tweets and Facebook containing over 200 thousand pictures, and over 40 thousand fresh posts on a Tumblr blog within 72 hours of its creation. The term "Big Data" was first introduced by researcher Roger Magoulas in 2005, referring to the handling of huge amounts of data through old-fashioned DBMS methods or alternative techniques.

Big Data originates from various sources, including smartphones, sensors, social media sites, and search queries. It is characterized by its vast size, collected from diverse and autonomous facts, and cannot be handled using outdated DBMS methods [3]. Analyzing Big Data presents significant complexity, requiring specialized tools for analysis. These tools have been designed to consolidate and operate all data (facts), replacing outdated DBMS methods. This paper aims to provide a comprehensive overview of the four most common Big Data structures, namely Apache Flink, Storm, Spark, and Hadoop. The authors use a fixed set of Key Performance Indicators (KPIs) derived from literature analysis to compare these frameworks [4].

The paper is structured into different parts, beginning with an introduction to the special features of Big Data, known as the "Vs of Big Data." The paper then proceeds to discuss the different Big Data structures, followed by a comparative analysis of their performance. Finally, the paper concludes with a summary of key findings.

The comparison of Big Data structures is crucial in selecting the most appropriate framework for specific applications. The authors emphasize the importance of KPIs, as they serve as a guide for researchers and practitioners when selecting the appropriate framework for their needs. The paper's contribution lies in its comprehensive analysis of the different Big Data structures, providing a clearer understanding of their respective strengths and weaknesses [5]. This paper highlights the significance of Big Data analytics, which has become a critical tool for analyzing vast amounts of data. The authors provide a comprehensive overview of the most common Big Data structures and a comparative analysis of their performance [6]. The paper's findings will be valuable for stakeholders, researchers, and practitioners in choosing the most suitable framework for their projects, ultimately improving Big Data processing and analytics. Future research can build upon this paper's findings by further exploring the performance of different Big Data structures, possibly using different KPIs or different evaluation methods [7]. Furthermore, future studies can investigate the effectiveness of combining different Big Data structures, using hybrid or distributed systems, to improve overall performance. This paper's limitations include the focus on only four Big Data structures, limiting the generalizability of the findings to other frameworks [8]. Moreover, the authors did not evaluate the frameworks' cost-effectiveness, which is an essential factor to consider in real-world applications [9]. Additionally, the paper did not consider the impact of different data sizes, types, or formats, which could affect the frameworks' performance.

In conclusion, this paper provides a valuable contribution to the literature on Big Data analytics by offering a comprehensive comparison of the most common Big Data structures [10]. The findings can assist stakeholders in making informed decisions when selecting the appropriate framework for their projects, ultimately improving Big Data processing and analytics. The paper's limitations suggest areas for future research and expansion of the current findings.

## 2. METHODOLOGY

Methodology:

To achieve the objectives of this study, a literature review was conducted to collect and analyze relevant data on the performance of four commonly used Big Data frameworks, namely Apache Flink, Storm, Spark, and Hadoop [11]. The literature review involved searching various databases, including Google Scholar, IEEE Xplore, ACM Digital Library, and ScienceDirect. The search was limited to studies published in English and between 2010 and 2021.

The search terms used were "Big Data," "Apache Flink," "Apache Storm," "Apache Spark," and "Apache Hadoop." The inclusion criteria included studies that compared the performance of the four Big Data frameworks based on predefined KPIs [12]. Additionally, studies that evaluated the performance of the frameworks in different application scenarios were also included. Studies that did not provide empirical data or used outdated versions of the frameworks were excluded.

The collected data were analyzed using a qualitative approach, where the results were interpreted in a descriptive narrative format. The study's primary outcome was the comparison of the frameworks based on the selected KPIs, which included processing time, CPU usage, latency, throughput, execution time, sustainable concurrency level, task performance, scalability, and fault tolerance [13], [14]. The KPIs were chosen based on their relevance to the performance of Big Data frameworks, and their measurement was based on the standard metrics used in the literature.

The literature review process involved three stages: screening, eligibility assessment, and data extraction. The screening process involved scanning the title and abstract of each study to identify potentially relevant articles [15]. The eligibility assessment involved a full-text review of the selected articles to ensure they met the inclusion criteria. The data extraction stage involved extracting relevant information from the eligible studies, including the KPIs, study design, sample size, data type, and data processing methods [16]. This study utilized a literature review approach to compare the performance of four commonly used Big Data frameworks. The study's methodology involved a comprehensive search of relevant databases, a predefined set of inclusion criteria, and a qualitative approach to analyze the collected data [17], [18]. The study's primary outcome was the comparison of the frameworks based on predefined KPIs, which were selected based on their relevance to the performance of Big Data frameworks. To begin with, the methodology of this study aimed to achieve the objectives of comparing the performance of four widely used Big Data frameworks, namely Apache Flink, Storm, Spark, and Hadoop. The literature review method was chosen as it is an effective way to collect and analyze relevant data from existing studies [19]. The literature review process involved searching various databases such as Google Scholar, IEEE Xplore, ACM Digital Library, and ScienceDirect.

The search was limited to studies published in English between 2010 and 2021, ensuring that the collected data were current and relevant. To narrow down the search, specific keywords were used, including "Big Data," "Apache Flink," "Apache Storm," "Apache Spark," and "Apache Hadoop." The inclusion criteria were set to ensure that the selected studies were suitable for the comparison of Big Data frameworks. Studies that compared the performance of the four Big Data frameworks based on predefined KPIs were included. Additionally, studies that evaluated the performance of the frameworks in different application scenarios were also included. Studies that did not provide empirical data or used outdated versions of the frameworks were excluded.

After selecting the relevant studies, a qualitative approach was used to analyze the collected data. The primary outcome was the comparison of the frameworks based on predefined KPIs. The selected KPIs included processing time, CPU usage, latency, throughput, execution time, sustainable

concurrency level, task performance, scalability, and fault tolerance [20]. These KPIs were chosen based on their relevance to the performance of Big Data frameworks, and their measurement was based on the standard metrics used in the literature. The literature review process involved three stages, including screening, eligibility assessment, and data extraction. In the screening stage, the title and abstract of each study were scanned to identify potentially relevant articles [21]. In the eligibility assessment stage, a full-text review of the selected articles was conducted to ensure they met the inclusion criteria. In the data extraction stage, relevant information such as KPIs, study design, sample size, data type, and data processing methods were extracted from the eligible studies.

In conclusion, the methodology of this study involved a literature review approach that aimed to collect and analyze relevant data on the performance of four commonly used Big Data frameworks [22]. The inclusion criteria were set to ensure that the selected studies were suitable for comparison, and a qualitative approach was used to analyze the collected data [23]. The selected KPIs were chosen based on their relevance to the performance of Big Data frameworks, and the literature review process involved three stages, including screening, eligibility assessment, and data extraction.

## 3.RESULTS:

The results of this study showed that Apache Spark was the best-performing framework across all the predefined KPIs. The comparison of the four Big Data frameworks based on the selected KPIs revealed significant differences in their performance [24], [25]. Regarding processing time, Apache Spark had the lowest processing time, followed by Apache Flink, Storm, and Hadoop. For CPU usage, Apache Spark and Flink had the lowest usage, while Storm and Hadoop had the highest. For latency, Apache Spark had the lowest latency, while Storm and Hadoop had the highest. In terms of throughput, Apache Spark had the highest throughput, followed by Flink, Storm, and Hadoop [26].

Regarding execution time, Apache Spark had the lowest execution time, followed by Flink, Storm, and Hadoop. For sustainable concurrency level, Apache Spark and Flink had the highest concurrency level, while Storm and Hadoop had the lowest [27], [28]. For task performance, Apache Spark and Flink had the best task performance, while Storm and Hadoop had the worst. Regarding scalability, Apache Spark and Flink had the highest scalability, while Storm and Hadoop had the lowest [29]. For fault tolerance, Apache Flink had the highest fault tolerance, followed by Storm, Spark, and Hadoop.

The results of this study showed that the selection of the appropriate Big Data framework depends on the specific application requirements. However, overall, Apache Spark was the best-performing framework across most of the selected KPIs. The results of this study align with previous research that has also shown Apache Spark to be a high-performing Big Data framework [30]. However, the study's findings also suggest that Apache Flink could be a suitable option for stream processing applications due to its high fault tolerance and task performance [31].

Additionally, the study's results reveal the importance of considering multiple KPIs when evaluating the performance of Big Data frameworks. The selected KPIs in this study provided a comprehensive evaluation of the frameworks' performance, considering factors such as processing time, CPU usage, latency, throughput, execution time, sustainable concurrency level, task performance, scalability, and fault tolerance. The study's results also suggest the need for further research to investigate the cost-effectiveness of the different frameworks, as this is an essential factor to consider in real-world applications. Moreover, future research could explore the impact of different data sizes, types, or formats on the performance of the frameworks.

In conclusion, the results of this study provide valuable insights into the performance of different Big Data frameworks, which can assist stakeholders in making informed decisions when selecting the appropriate framework for their projects. The study's findings suggest that Apache Spark is the best-performing framework across most of the selected KPIs, while Apache Flink could be a suitable option for stream processing applications. The results of this study provide valuable insights into the performance of different Big Data frameworks. The findings can assist stakeholders in making informed decisions when selecting the appropriate framework for their projects, ultimately improving Big Data processing and analytics.

## 4. CONCLUSION

The purpose of this study was to compare the performance of four commonly used Big Data frameworks, namely Apache Flink, Storm, Spark, and Hadoop. The study's methodology involved a literature review approach, and the collected data were analyzed using a qualitative approach. The primary outcome was the comparison of the frameworks based on predefined KPIs, including processing time, CPU usage, latency, throughput, execution time, sustainable concurrency level, task performance, scalability, and fault tolerance. The study's results revealed significant differences in the performance of the four Big Data frameworks. Apache Spark was the best-performing framework across most of the selected KPIs. However, Apache Flink was found to be a suitable option for stream processing applications due to its high fault tolerance and task performance.

The findings of this study have several implications for stakeholders involved in Big Data processing and analytics. First, the results suggest that the selection of the appropriate Big Data framework depends on the specific application requirements. Stakeholders should consider the specific KPIs relevant to their projects when selecting a framework. Second, the study's results highlight the importance of considering multiple KPIs when evaluating the performance of Big Data frameworks. The selected KPIs in this study provided a comprehensive evaluation of the frameworks' performance, considering factors such as processing time, CPU usage, latency, throughput, execution time, sustainable concurrency level, task performance, scalability, and fault tolerance. Moreover, the study's findings suggest the need for further research to investigate the cost-effectiveness of the different frameworks. While this study focused on the performance of the frameworks, the cost-effectiveness of the frameworks is also a crucial factor to consider in real-world applications. Future research could explore the costs associated with using the different frameworks and compare them to their performance. Additionally, future research could explore the impact of different data sizes, types, or formats on the performance of the

frameworks. The data used in this study were limited to specific types and sizes, and future studies could expand the scope of the analysis to include more diverse data.

In conclusion, this study provides valuable insights into the performance of different Big Data frameworks. The results suggest that Apache Spark is the best-performing framework across most of the selected KPIs, while Apache Flink could be a suitable option for stream processing applications. The findings of this study have important implications for stakeholders involved in Big Data processing and analytics. They can assist in making informed decisions when selecting the appropriate framework for their projects, ultimately improving Big Data processing and analytics.

Overall, this study contributes to the ongoing efforts to optimize Big Data processing and analytics. As Big Data continues to grow and expand, selecting the most suitable framework is critical to ensure efficient and effective processing of data. The results of this study can aid in the development of more robust Big Data frameworks and ultimately contribute to the advancement of the field of Big Data processing and analytics.

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