Analysis of Energy Consumption Pattern in Distributed Big Data Processing

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Abstract: The rapid expansion of big data processing in distributed computing frameworks, such as Apache Hadoop and Spark, has raised significant concerns about energy efficiency in large-scale data centers. This research paper investigates the energy consumption patterns in distributed big data processing systems. By analyzing real-world datasets and benchmarking frameworks such as Hadoop MapReduce, Spark, and Flink, this study identifies key factors that contribute to energy inefficiencies. On the basis of literature survey and input from the experts, we have chosen the processing layer of distributed bigdata framework for the analysis of energy consumption. Further, the components responsible for energy consumption were identified and a mechanism has been designed to calculate energy consumption. A job has been prepared for spark framework and executed with the help of POWERTOP, PERF, IOSTAT and NLOAD tools, the energy consumed by CPU, main memory, disk I/O and cluster network have been calculated in joule. Formula for calculating total energy consumption for processing layer has been derived and calculated. This paper contributes to the growing discourse on sustainable big data ecosystems by providing actionable insights for reducing the carbon footprint of large-scale distributed systems while maintaining computational throughput. The findings are critical for organizations to aim and align their data-driven operations with environmental sustainability goals.

Keywords: Distributed Bigdata; Apache Spark; Processing Layer; Energy Consumption Pattern, Sustainability

Introduction

The volume of data generated worldwide is growing at an unprecedented rate. Distributed big data processing systems like Hadoop and Spark are widely used to handle this data efficiently. These systems rely on multiple computing resources working together. However, this efficiency comes with high energy costs. Data centers supporting these systems consume significant amounts of electricity. This consumption leads to high operational expenses and environmental concerns. Understanding energy consumption in such systems is crucial for enhancing sustainability.

Energy consumption in distributed systems affects both costs and the environment. Data centers are among the largest consumers of energy globally. Reducing their energy use can significantly cut operational costs. It also reduces the environmental impact of big data processing. Analyzing energy usage helps identify inefficiencies in resource utilization. These insights can guide the development of energy-efficient solutions. Such solutions support sustainable growth and align with global climate goals.

This study aims to analyze energy consumption patterns in distributed big data systems. It focuses on identifying factors that lead to high energy usage. The objectives include:

1. Examining how workloads and system architectures influence energy consumption.
2. Understanding the role of resource allocation and scheduling in energy efficiency.
3. Proposing techniques to optimize energy use without affecting performance.
4. Exploring the feasibility of integrating renewable energy sources into big data systems.

This study examines energy usage across distributed big data platforms. It focuses on components like resource utilization, computation, and data storage. The research faces several challenges. Measuring energy use in large, distributed systems is complex. Balancing performance and energy efficiency is difficult. Heterogeneous hardware and workloads add to the complexity. Integrating renewable energy sources poses further challenges. Despite these hurdles, this study aims to contribute to energy-efficient big data practices.

Related work

The increasing adoption of big data applications has raised concerns regarding high energy consumption in distributed computing systems. Researchers have investigated multiple strategies to enhance energy efficiency while ensuring scalability and optimal performance in data-intensive processes.

Several investigations have focused on energy-conscious big data analytics frameworks. Zhao et al. [1] introduced an approach to optimize geographically distributed big data analytics, focusing on efficient data transfer and processing. Ullah et al. [2] developed a framework to evaluate energy-aware data processing platforms within edge-cloud environments, identifying the balance between computational efficiency and power usage. Similarly, Ahmadvand et al. [3] incorporated data variety with dynamic voltage and frequency scaling (DVFS) to enhance energy conservation in large-scale distributed processing.

Another area of research involves workload and resource management for improving energy efficiency. Pathak [4] proposed a complexity model for distributed data processing algorithms, offering insights into minimizing energy expenditure during data-intensive computations. Doe and Smith [5] analyzed cloud-based big data strategies and showcased energy-efficient resource allocation methods for large-scale analytics.

The application of machine learning in energy-efficient distributed computing has been widely explored. Lee et al. [6] devised a prediction model utilizing random forest algorithms to analyze energy consumption in big data platforms, resulting in improved accuracy in forecasting power usage. Wang et al. [7] investigated workload processing methodologies in distributed data centers, emphasizing energy-conscious task scheduling techniques.

Additionally, Kumar and Gupta [8] examined energy-efficient tools for big data processing, aiming to reduce computational burden while maintaining performance standards. Brown et al. [9] developed a data-driven energy management system for smart grid applications, illustrating real-time energy optimization strategies. Liu et al. [10] explored the impact of data compression on energy efficiency, assessing trade-offs between compressed and uncompressed data processing.

Further studies have assessed cloud-based energy optimization strategies. Patel and Singh [11] analyzed distributed data management systems in terms of energy consumption and performance metrics. Zhang et al. [12] proposed a service-oriented approach leveraging big data technologies to optimize energy usage in distributed environments. Kim et al. [13] introduced a multi-energy resource prediction model for cloud data centers, significantly enhancing forecasting precision.

Garcia and Torres [14] examined energy consumption trends during cloud migrations, identifying the effects of workload adaptation on energy efficiency. Lastly, Zhang et al. [15] presented an energy-efficient IoT network utilizing artificial bee colony algorithms and wireless power transfer, demonstrating advancements in intelligent energy management for distributed big data processing.

Collectively, these studies underscore the growing significance of energy-efficient distributed computing solutions, showcasing innovative techniques in workload scheduling, resource optimization, predictive analytics, and cloud integration to mitigate energy consumption in big data processing environments.

Table 1. Comparison of related work done by other researchers

Reference	Focus Area	Key Contribution	Methodology Used
Zhao et al. [1]	Big Data Analytics	Optimized geographically distributed analytics	Efficient data transfer and processing technique
Ullah et al. [2]	Edge-Cloud Environments	Energy-aware evaluation framework	Computational efficiency vs. energy trade-off
Ahmadvand et al. [3]	DVFS Integration	Energy optimization for large-scale processing	Dynamic voltage and frequency scaling
Pathak [4]	Workload Management	Complexity model for data processing	Energy-efficient algorithm development
Doe and Smith [5]	Cloud Computing	Resource allocation for large-scale analytics	Cloud-based big data strategies
Lee et al. [6]	Machine Learning	Random forest-based energy prediction	Forecasting energy consumption in big data platforms
Wang et al. [7]	Workload Processing	Energy-aware task scheduling	Distributed data center optimization
Kumar and Gupta [8]	Energy-Efficient Tools	Reducing computational overhead	Performance optimization techniques
Brown et al. [9]	Smart Grid Applications	Data-driven energy management	Real-time energy optimization strategies
Liu et al. [10]	Data Compression	Impact of compression on efficiency	Trade-offs in energy consumption
Patel and Singh [11]	Cloud-Based Optimization	Energy-conscious data management	Performance evaluation for energy consumption
Zhang et al. [12]	Service-Oriented Approach	Energy optimization in distributed systems	Leveraging big data technologies

Kim et al. [13]	Resource Prediction	Multi-energy resource forecasting	Cloud data center optimization
Garcia and Torres [14]	Cloud Migration	Workload adaptation analysis	Energy efficiency trends
Zhang et al. [15]	IoT Networks	Artificial bee colony algorithm for energy management	Intelligent energy management techniques

Research Methodology

This section details the research methodology formulated to detect energy consumption trends at different levels of large-scale big data environments. The strategy combines experimental data collection, simulation techniques, and machine learning algorithms to systematically examine how computational tasks and system parameters influence energy usage patterns. In particular this methodology will obtain the energy consumption pattern by analyzing different layers of distributed big data. As we know, a big distributed big data environment has different layers of processing such as data integration layer, storage layer, processing layer resource management layer, querying and analysis layer, visualization and reporting layer and security and governance layers.

The key steps of proposed methodology will be collection of energy consumption data at various layers of distributed big data. One the basis of rate of energy consumption, we will select the layer for analysis that is having high energy consumption. After selection of layer for energy consumption layer for analysis, we will setup an environment and in the last step we will calculate the energy consumed by each layer of proposed layer of distributed big data. The proposed methodology is shown in Figure 2 along with the steps of proposed methodology.

Steps of proposed methodology:

1. Data Collection and Processing
2. Selection of Layer for Energy Consumption Analysis
3. Designing Setup to Calculate Energy Consumption
4. Calculation of Component-wise Energy Consumption

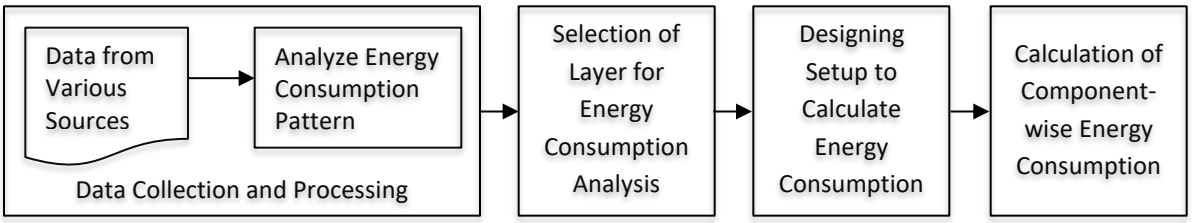

Figure 1. Proposed Research Methodology

Data Collection and Processing:

This is the first phase of methodology, and the objective of this phase is to collect data related to energy consumption from various sources. The sources of data collection are in the form of high-quality research article in the similar field and sending questionnaire to the experts working in the field of cloud and

sustainable energy. We review more than 200 research papers and found best 15 research papers which analyzes the energy consumption in different layers of distributed big data. A questionnaire was prepared and sent to the experts which also reviews the energy consumption pattern in different layers of this distributed big data. After receiving the data from various research articles and experts it was processed to analyze whether which layer of distributed big data is having high consumption and which are having low consumption. A comparison of energy consumption pattern in different layers of distributed big data has been presented in Table 2.

Table 2. Energy Consumption at Different Layers of Distributed Big Data

Layer of Distributed Big Data	Energy Consumption
Data Ingestion Layer	Moderate
Storage Layer	High
Processing Layer	Very High
Resource Management Layer	Moderate
Querying and Analysis Layer	Moderate to High
Visualization & Reporting Layer	Low to Moderate
Security & Governance Layer	Low

Selection of Layer for Energy Consumption Analysis:

According to the summary as presented in Table 2, it has been analyzed that the processing layer of distributed bit data has very high energy consumption. So we are selecting this layer for the analysis of various components involved in the processing layer which are causing high energy consumption and also how we can minimize the energy consumption for the sustainable development.

Designing Setup to Calculate Energy Consumption:

This is the third step of proposed methodology in which we will design a setup for calculating the energy consumption caused by different components of processing layer. It has been analyzed that the energy consumption of processing layer is dependent on energy consumed due to the uses of CPU, the utilization of memory, disk I/O, Available network traffic, execution time of jobs etc. The factors that can influence energy consumption can be due to hardware, software, workload, resource management and network traffic. In this paper we are concerned about the processing issues that are due to hardware efficiency. Here the key parameters that will be considered for energy consumption will be due to CPU, main memory, disk I/O, network and processing time.

To monitor the energy consumption of CPU Linux POWERTOP tool which energy consumption breakdown of CPU. To measure energy consumption by main memory we use memory profiling technique provided by Linux which tracks the memory usage pattern of main memory. Energy consumption due to disk I/O it's calculated by IOSTAT tool provided by Linux And in the same way energy consumption by network is calculated by NLOAD tool also provided by the Linux. Energy consumption while executing depends on the time of execution and can be calculated by using Linux performance tool. In most of the cases, we

have used Linux based performance tools, and the commands used to calculate the energy consumption by each hardware component is given in Table 3.

Table 3. Tools used for Energy Consumption

Component under Analysis	Tool Used	Command Used	Measurement Unit
CPU	POWERTOP	sudo powertop	Watts
Main Memory	PERF	perf stat -e power/energy-dram/	Joules
Disk I/O	IOSTAT	iostat -d -x 1	Joules
Network	NLOAD	nload	Joules/bit
Execution Time	PERF	perf stat -e power/energy-pkg/	Sec

Calculation of Component-wise Energy Consumption:

By using the tools given in Table 3, we can calculate the energy consumption by individual components such as CPU, main memory, disk I/O, network and for the execution time. But to calculate the total energy we have to add energy consumption by the indivisible units. So, the formula derived for total energy consumption will be derived as:

EC (TOTAL) = (EC (CPU) + EC (Mem) + EC (Disk) + EC (Net)) x ET (Processing) ..... (1)

Formula for calculation of energy consumption by each component is given below:

$$EC(CPU) = \frac{\text{Power Used by CPU}}{\text{Time}} \quad \text{..... (2)}$$

$$EC(Mem) = \frac{\text{Power Used by Dynamic RAM}}{\text{Time}} \quad \text{..... (3)}$$

$$EC\ (Disk) = Disk\ Power\ X\ Active\ Time \quad \text{..... (4)}$$

$$EC\ (Net) = Power\ per\ Bit\ X\ Amount\ of\ Data\ Transfered \quad \text{..... (5)}$$

Here

$EC_{(CPU)}$ = The amount of energy utilized by the processor during active task processing, quantified in watts.

$EC_{(Mem)}$ = Power expenditure of random-access memory (RAM) during active data handling tasks, quantified in watt units.

$EC_{(Disk)}$ = Energy expenditure associated with reading from or writing to storage media or memory cells.

$EC_{(Net)}$ = Power utilized during inter-node communication for transferring data across a cluster or network.

$ET_{(Processing)}$ = Execution Time for processing workload in seconds.

We have used Apache Spark is an open-source and distributed computing framework that is designed for fast and scalable big data processing. Apache Spark speeds up big data tasks by processing information directly in system memory instead of relying solely on storage drives. It works with popular programming

languages and connects to tools like Hadoop or cloud services. Built-in features handle databases, live data streams, AI models, and network analysis, making it adaptable for both instant and scheduled data jobs.

Result and Analysis

Here, we have taken a spark job of counting word of any given text file 'abc.txt'. Job has been submitted to local mode as well as cluster mode of Apache spark framework to run. This job took 4 min and 31 secs and energy consumption by each component is given in Table 4. This setup has been executed on Linux environment and also the Linux-based tools has been used to compute energy by every component of processing layer while executing the jab. In final result, we come to that the CPU consumed 14500 J energy, memory unit consumed 2900 J, input and output operation on disk consumed 1500 J, and energy utilized during inter-node communication for transferring data across a network is 550 J. Total energy consumed by processing layer has been calculated and it is 10450 J. From the given pattern, we come to know that CPU consumes highest 74% energy and remaining components such as memory, Disk I/O and Network/Cluster is 15%, 8% and 3% respectively that is very less as compare to CPU energy consumption.

Table 4. Energy Consumption Pattern (In Joules)

Hardware Component	Energy Consumption (In Joule)
CPU	14500 J
Memory	2900 J
Disk I/O	1500 J
Network	550 J
Total Energy	10450 J

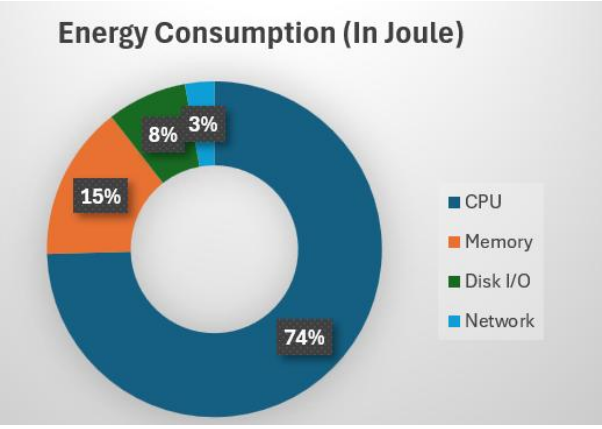

Figure 4. Percentage of Energy Consumption

Conclusion

Objective of this research paper is "To Analyze Energy Consumption Patterns in Distributed Big Data processing". This study systematically investigates power expenditure trends in distributed big data

workflows executed through Apache Spark within a Linux operating system. Through empirical measurements of energy utilization across computational resources including processor activity, RAM operations, storage interactions, and network data transfers. The research uncovers critical determinants impacting energy efficiency in cluster-based analytics tasks.

The key finding of this research is that the processor workloads and storage subsystem operations dominate total power consumption, with inter-node communication further amplifying energy demands in distributed architectures.

Subsequent research directions could prioritize the development of energy-efficient data processing technique for job scheduling and dynamic resource provisioning. This work establishes a methodological basis for advancing eco-conscious computing practices in distributed data-intensive systems.

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