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Waste Generated in Distributed Data Processing Systems: Strategies and Future Directions

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Abstract

Distributed Data Processing (DDP) is integral to modern cloud and edge computing environments. Additionally, it serves as a fundamental component of big data analytics, particularly for real-time analytics. Various frameworks such as Spark FSpark, spark flow, and Storm are designed for effective distributed data processing. However, DDP generates significant waste in terms of energy consumption, resource allocation, and data transmission. Efficiently managing these wastes is crucial for improving system performance and minimizing environmental impact. This paper explores various waste and their reduction strategies employed in distributed systems, focusing on energy- efficient scheduling, network optimization, and resource management techniques. The result indicates various wastes such as energy waste, improper or inefficient utilization or distribution of computational resources, carbon footprint waste, inefficient execution time, storage of unnecessary or duplicate data, and inefficient data transmission. Moreover, the study result also signifies that carbon- and energy-aware scheduling, task offloading, and data deduplication strategies show promising results in minimizing waste. The contribution of this paper lies in identifying waste, key approaches to waste reduction and offering insights into their practical applications in distributed data systems. The study will be useful for the researcher to extend the research by providing additional effective solutions or verifying the reported solutions in terms of waste minimization.

Keywords: Big Data Processing, Distributed Data Processing, Waste Reduction, Distributed System.

1. Introduction

Distributed data processing has emerged as the backbone of today's computing landscape as it makes large-scale data analytics, machine learning, and edge computing scalable, flexible, and high-performance. They are used in many areas in industries, including smart cities and healthcare, as well as cloud computing platforms. Nevertheless, the complex operation of such systems, as well as their constantly increasing size, has resulted in inefficient generation of large amounts of waste [1], [2], [3]. The various general reported terminologies of waste are presented in Table I. It is essential to control and reduce this waste, not only to enhance the performance of the system but also to minimize the environmental responsibility as well as the cost of the operations through the consumption of energy, use of resources, and transmission of data [3], [4],[5].

Table 1. Notation of Wastes from existing literature [6].

Definition	Reference
"Non- efficient way of working" or "Everything that does not make it to the release. "Activities that consume time, resources or space but does not add any value" or "Functions or features lying in the queue".	[7]
"Activities that absorb resources and increase cost without adding value".	[8]
"Waste can be non-value-adding activities (NVA), variations (in process quality, cost, delivery), and unreasonableness (overburden)".	[9], [10]

Although the significance of these distributed systems has increased lately, they usually have several forms of inefficiency that lead to excessive energy consumption, wastage of resources, and ineffective operation of these systems. When ignored, these inefficiencies have the potential to severely limit the capability of distributed data processing systems, diminish the sustainability of extensive computational activities, as well as environmental impact [1], [4], [11], [12]. There have been multiple strategies recently proposed to deal with these issues, and recent studies have proposed a range of strategies seeking to either deal with or evaluate these strategies [3], [13], [14], [15].

Besides the technical inefficiency, distributed systems can also experience the root cause of wastage due to organizational and human aspects, which are avoidable. As an example, it can be inefficient communication of requirements, the development of inappropriate features, or redundant complexity during the development of systems that cause waste even in technically advanced systems [6], [16]. Some of those problems that many people always ignore lead to inefficiencies, such as rework, delayed completion, and poor coordination. The resolution of such types of waste must be more comprehensive, as the structure of the algorithms and the design of the system should not be the only two aspects on which it is based, but also the workflow and communication within the team [6], [16].

Distributed systems need waste consideration. The problem of minimizing waste in distributed systems is not merely an issue of enhancing efficiency, but also of being green. The environmental impact of distributed systems only increases along with the overall over-dependence on cloud services, IoT gadgets, and big data analysis. Carbon lease of carbon dioxide, energy use, and loss of natural resources are urgent problems that need to be addressed in order for distributed systems to keep the digital economy alive without damaging environmental objectives [14], [17].

Additionally, on an operational perspective, minimization of waste is vital in enhancing the functioning of a system [16], [6]. Less power consumption, distribution of resources and data transmission delays add up to high-speed, stable, and more cost-effective systems. It is also possible to make hardware last longer and maintenance less expensive, which will result in the overall cheaper cost of ownership on the distributed systems [15], [18], [20]. The study aims to identify the various wastes in the context of distributed data processing, along with the solutions and strategies to manage the identified wastes.

The paper is organized as follows: Section 2 provides a review of the research area and existing literature in the context of waste. Section 3 covers the research methodology, whereas the study results are presented in Section 4. The conclusion and future work are discussed in 5 and 6 sections respectively

2. Background and Relevant Work

The Distributed data processing lies at the heart of recent computing trends. For instance, big data analytics, machine learning, and edge computing. They play a crucial role in major industrial venues like smart cities, healthcare and cloud computing platforms. Nevertheless, the complex operation of such systems, as well as their constantly increasing size, has resulted in inefficient generation of large amounts of waste [1], [2], [3].

Waste exploration and minimization research has its roots in the 1980s, when Toyota used a lean manufacturing approach to reform the automobile industry [19]. Afterwards, Lean manufacturing strategy was explored by a number of researchers [6], [20], [21]. The seven categories of waste for business and manufacturing processes were introduced by [22], [23]. Later, the eight wastes of the Toyota production system were recognized by [21]. In early 2000, the lean principle moved from manufacturing to the computing domain [24].

Multiple studies have been conducted with the aim of exploring waste emergence in various fields following the lean principles and practices for process optimization and product development [7], [8], [9], [16], [25], [26]. The primary objective of the lean approach is the detection and minimization of waste [7], [9]. The notion of waste identification and mitigation is little explored in the context of distributed data processing literature [7].

It is argued that the use of energy can be a major source of waste in distributed systems [1], [26]. It is also conveyed that inefficient data transmission across distributed networks often leads to wasted bandwidth and increased energy consumption [3], [13]. Likewise, inefficient utilization or distribution of computational resources like CPU, memory, storage and network bandwidth and data duplication can act as a waste [2], [4]. It is reported that if the wastes are left unattended, they can affect the capability of distributed data processing systems, reduce the sustainability of widespread computational activities, as well as environmental impact [1], [4], [11], [12], [26].

The existing research also reported various strategies to minimize waste in the context of distributed data processing. For instance, optimal routing algorithms facilitate the minimization of data transmission by minimizing travel distances and energy consumption [27]. Likewise, DVFS and power management techniques can work to decrease their energy drainage during idle time so that there is only utilization of energy when systems need it [28]. Additionally, data compression lessens packet sizes, which keeps unnecessary bandwidth back and reduces latency [29].

To the best of our knowledge, no recent studies have focused specifically on the identification of waste in the context of distributed data processing. This study is original in the context of waste identification and reduction for distributed data processing.

3. Research Methodology

This Systematic Literature Review (SLR) is utilized as directed by [30] to identify a unique list of distributed data processing wastes and their minimization strategies.
Research studies published between 2020 and 2025 were considered for the study. In total, 32 studies were considered for waste identification and waste reduction strategies.

3.1 Study Research Questions

The intended research questions are given in Tables 2 and 3.

Table 2. Research Questions.

Sr. No	Title 2
RQ1	What are the different types of waste produced in distributed data processing systems.
RQ2	What strategies are currently being used to reduce energy, network, and storage waste in these systems?

Table 3. Research Objectives [6].

Sr. No	Title 2
RO 1	To identify and classify the types of waste in distributed data processing systems.
RO 2	To analyze and evaluate current strategies for reducing energy, network, and storage waste.

3.2. Search String

The search string is defined based on essential key terms. The core keywords and their alternative word are represented in Table 4.

Table 4. Key Words and Alternative Words

Key Terms	Alternative Key Term
Distributed Data Processing	Distributed Systems, Big Data Processing
Wastes	Lean, Valueless, Inefficient
Actions	Events, Happening
Solutions	Approaches, Strategies, Mitigation

The search string used to answer the research questions is ((“Distributed Data Processing” OR “Distributed System” OR “Big Data Processing” AND (“Waste” OR “Valueless” OR “Lean” OR “Inefficient”) OR (“Approaches” OR “Solutions” OR “Strategies OR “Mitigations”

3.3 Data Source

The databases such as IEEE, Springer, ACM and Wiley were considered for study selection. The existing studies from 2020 to 2025 were considered for the review study.

3.4 Selection Process of Study

The dual-step process is incorporated to select the required studies. The initial one is the inclusion and elimination criteria that were used to get the required research papers in the context of distributed data processing. Then the citations of primary studies were further considered for related studies. The articles representing only conference information or general reports were excluded. The duplicate papers available in different general categories were considered for only one instance. The research studies before 2020 and after 2025 were not considered for the study. The guidelines provided by [30] were utilized for this purpose. In total, 32 studies were selected after quality assessment for the study.

3.5 Data Extraction

As per the guidelines given by [32], data was extracted to manage the record of waste produced during distributed data processing. The selected primary studies were explored for the identification of waste generated during distributed data processing. Moreover, the selected research articles were also explored for strategies reported to minimize the identified distributed data processing wastes.

3.6 Data Organization

The extracted data was organized using thematic Analysis to identify the unique list of wastes and their minimizing strategies [30].

4. Results

The study results report 14 unique DDP waste categories to answer the research question (RQ1): "What are the different types of waste produced in distributed data processing systems?" The included wastes are Energy Wastes [4], [17], [27], [33], [34], Data Transmission Waste [9], [11], [22], [29], Resource Waste [1], [33], [44], [45], Carbon Footprints Waste [3], [27] [35], [36], [46], Extraneous Processing Time Waste [3], [4], [48], [50], Storage Waste [37], [39], Network Congestion Waste [13], [46], [48], [52], Redundancy Waste [39] [44], [53], Inefficient Scheduling Waste [49], [50], [54], Design Waste [53], Tasks and Time Wastes [44], [47], [50], Rework Waste [53], Human Coordination Waste [48], [53] Waiting and Latency Waste [4], [13], [34]. The outcome of RO1 is presented in Table 3. Moreover, for each identified waste, the study results report strategies to minimize it. Likewise, Load Balancing [34], [40], [44], [47], Task Offloading [36], [41], [50]. Genetic Algorithms [49], [50], and Data Compression [39] strategies can minimize energy waste. The outcome of RO 2 is presented in Table 4. The study result shows that considerable work is done to minimize the waste; however, limited work is done to minimize the wastes such as Carbon Footprint Waste, Network Congestion Waste, DDP system Design wastes, Rework Waste, Human Coordination Waste in the context of distributed data processing [48], [53]. Figure 1 gives the visual view regarding opportunities to work for waste categories that are little explored by the investigators.

Table 5. Waste Generated During DDP

Waste ID	Waste Type	Reference
DDPW-1	Energy Waste	[1], [2], [3], [4], [17], [27], [28], [33], [34], [35], [36], [37], [38], [39], [40], [41], [42], [43]
DDPW-2	Data Transmission Waste	[9], [11], [29]
DDPW-3	Resource Waste	[1], [17], [33], [34], [37], [38], [39], [43], [44], [45]
DDPW-4	Carbon Footprint Waste	[3], [4], [27], [35], [36], [46]
DDPW-5	Extraneous Processing Time Waste	[3], [4], [17], [34], [36], [40], [41] [44], [47] , [48], [49], [50]
DDPW-6	Storage Waste	[44], [53], [29]
DDPW-7	Network Congestion Waste	[13], [51], [52]
DDPW-8	Redundancy Waste	[35], [44], [53]
DDPW-9	Inefficient Scheduling Waste	[2], [3], [17], [34], [36], [38], [40], [41], [44], [47], [49], [50], [54]

DDPW-10	Design Related Waste	[53]
DDPW-11	Tasks and Time Wastes	[3], [17], [34], [36], [40], [41] [44], [47] [49], [50]
DDPW-12	Rework Waste	[53]
DDPW-13	Human Coordination-Waste	[53]
DDPW-14	Waiting and Latency Waste	[4], [13], [34], [36],[51], [52]

Table 6. Strategies for Waste Minimization.

Waste ID	Strategies	Reference
DDPW-1	Energy Aware Scheduling	[1], [2], [4], [17], [34], [38], [39], [40], [41], [54]
	DVFS (Dynamic Voltage and Frequency Scaling)	[17], [28], [54]
	Workload Consolidation	[1], [17], [27], [34], [39]
	Renewable Green Energy Integration	[3], [33], [35], [37]
	Hybrid Scheduling	[2], [4], [41], [54]
	Passive & Active Cooling	[33]
	Waste heat reuse	[27], [37]
DDPW-2	Data Compression	[13], [51]
	Optimized routing	[51], [52]
	Federated learning efficiency	[45]
	Decision-tree– based transfer optimization	[13]
DDPW-3	Efficient VM Allocation	[1], [17], [34], [38]
	Auto-Scaling	[33], [34], [39]
	Cooperative Resource Sharing	[2], [17]
	Hybrid Optimization	[37], [44], [45]
DDPW-4	Carbon-Aware Scheduling	[3], [4], [27], [35], [36], [46]
	Waste Heat Reuse	[27], [37]
	Green Energy Integration	[35], [46]
DDPW-5	Load Balancing	[17], [34], [36], [40], [44], [47]
	Task offloading	[36], [41], [50]
	Precedence-aware scheduling	[4]
	Distributed cluster optimization	[2], [17]
	Genetic Algorithms	[41], [48], [49], [50]
DDPW-6	Data Deduplication	[39], [44]
	Data Compression	[39]
	Tiered Storage	[39]
	Efficient Storage Frameworks	[39], [44]
DDPW-7	Traffic Engineering	[51], [52]
	Congestion-Aware Routing	[13], [51]
	Collaborative Cluster Communication	[2]
DDPW-8	Duplicate Elimination	[39], [44]
	Lean Processes	[53]
	Avoiding Unnecessary	[35]

	Features	
DDPW-9	AI-based Scheduling	[3], [17], [34], [38], [40], [41], [49], [50]
	Genetic Algorithms	[41],[48],[49], [50]
	Hybrid Schedulers	[2], [4] , [41] [54]
	Energy-Aware Workflow Optimization	[1], [17], [34]
DDPW-10	Requirement Validation	[53]
	Lean Software Design	[53]
	Avoiding Over- Engineering	[35]
DDPW-11	Agile Methods	[53]
	Efficient task Management	[34], [36], [44], [17], [47]
	Genetic Algorithms	[48], [49], [50], [41]
	Workflow Optimization	[17], [40], [55]
DDPW-12	Continuous Integration	[53]
	Automated Testing	[53]
	Rework Prevention	[53]
DDPW-13	Improved Collaboration	[53]
	Coordination Frameworks	[48], [53]
	Reducing Communication Overhead	[48], [53]
DDPW-14	Network Optimization	[4], [13] [34], [36], [46] , [51] [52]
	Caching	[51], [52]
	Federated Scheduling	[4], [45]
	Latency Reduction Techniques	[13], [52], [56]

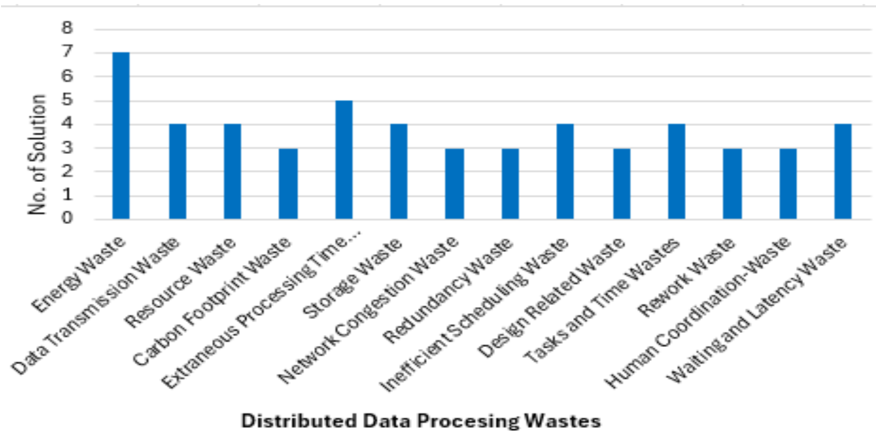

Figure 1. Distributed Data Processing Wastes

5. Conclusions and Future Work

The conducted study presented a unified list of wastes that can be generated during distributed data processing, along with the strategies that can be employed to reduce the reported wastes. The SLR methodology is used to identify the wastes and strategies to minimize them. The study reported 14 unique wastes in the context of distributed data processing. The conducted study explored various strategies to minimize the identified wastes. For instance, energy-aware scheduling, workload consolidation, and renewable green energy integration are used to minimize energy waste. Likewise, data deduplication, tiered storage, and efficient storage frameworks are used for minimizing storage waste. The study results show that human coordination waste, rework waste, carbon footprint waste, network congestion waste, distributed system design waste, waiting and latency, and redundancy wastes are explored to a lesser extent and provide future work opportunities. In future, it is planned to extend this study by validating the results from the industry.

6. Contribution

Big data is distributed and needs processing in real time. This study has a dual contribution towards big data processing distributed to multiple locations. The first one is the identification of a unique list of waste generated during distributed data processing. The second contribution is the identification of strategies to minimize the reported waste. The conducted study can help the researcher extend the research and the big data processing experts to work while focusing on the identified wastes.

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Abbreviations

The following abbreviations are used in this manuscript:

DDP	Distributed Data Processing
DDPW	Distributed Data Processing Wastes
NVA	Non-Value Added

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