Chapter 1
Introduction

1.1Introduction

In our daily digital society, data has turned into valuable assets across many industries, however, data possess different challenges with difficulties, particularly in the context of IoT. As cloud storage solutions become frequently flexible substitute for traditional storage solutions. Storing capacity in the cloud is an easy solution for applications that are connected and linked to the Internet of Things because, it offers an huge quantity of capacity, accessibility, and security as well. In conclusion, the result of the combination of artificial intelligence which is known throughout the world (AI) and also cloud platforms, the potential of Internet of Things which can be written as (IoT) data is further expanded, which makes easy way effective mining and analysis. In the Internet of Things called (IoT), integrated intelligence makes it possible for detectors for collecting and analyzing data or information, which in turn transforms operations in a very wide and vast range of businesses and companies. To process and storing this information and info with greater ease cloud storage make it possible , which may result in opening the door to new opportunities and chances for improved operations and insights. [1] Cloud storage provides a number of benefits in the context of the Internet of Things; nevertheless, Particularly with regard to security, and administrative control, it has a number of downsides. Therefore it is more risky too because, when confidential information is handed to third-party vendors, there is a significant risk that the data will not be protected and will not be accurate which is noteworthy. Furthermore, In addition, problems such as the transfer of info and the dependence on internet connectivity need to be tackled simultaneously. [2] Although, A number of advantages are provided by cloud storage, such as cost-effectiveness, scalability, and disaster recovery, but similarly on the other hand it has disadvantages too, such as

the inability to govern info, being locked in with a single vendor, and also common connectivity issues. Considering incorporating cloud storage options into applications for the Internet of Things organizations, they should be aware of both the benefits (advantages and disadvantages) and the limitations associated with each option. [3] In a nutshell, fundamentally revolutionize the way data management is handled in Internet of Things systems cloud storage has the ability, in the same manner, it also has the ability to ensure both advantages and downsides. Enterprises are able to leverage cloud storage to fully realize the possibilities of Internet of Things (IoT) data, while simultaneously guaranteeing security and efficacy in their activities and processes. This is accomplished by careful evaluation of its repercussions and resolution of any potential drawbacks the organization may encounter. [4]

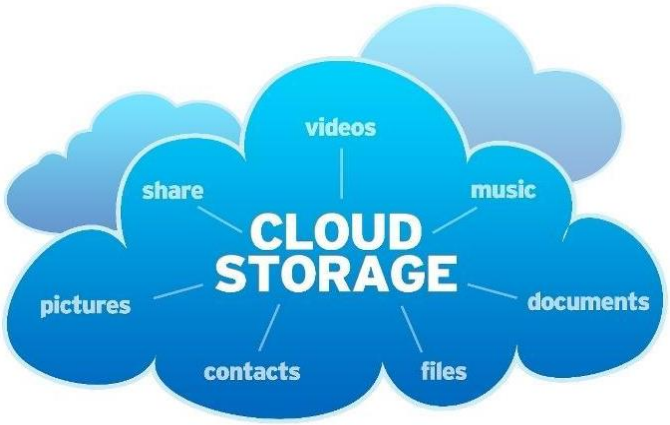

Figure 1.1: Cloud Storage [3]

The intersection of Internet of Things (IoT) and cloud storage, explores IoT devices' data generation and transmission to cloud servers, emphasizing key components like sensor networks, edge computing, and cloud infrastructure, functions such as data aggregation, processing, and storage in the cloud are analyzed for their efficiency, security, and scalability. The study aims to uncover strategies for optimizing IoT-cloud interactions, addressing challenges like latency, bandwidth, and privacy concerns.

1.2 Storage mechanism of Cloud

As the cloud have limited amount of storing capacity, so the use of duplicate data makes the system to used up and cause problems when it comes to handle the data. Data deduplication is the best method that researchers have found for addressing issue, however they have looked into many different approaches. To enhance storage, the method known as data deduplication was created [77]. This tactic is being employed by a number of cloud service providers, such as Dropbox, Amazon S3, and Google Drive. Making sure that data is never uploaded to the cloud more than once helps avoid data duplication.

A. The requirement for more storage capacity increases as the volume of digital data increases.

B. There is no built-in safeguard against duplicate data being stored in traditional solutions.

C. Data De-duplication is critical for removing redundant data and lowering storage costs.

The quantity of data generated is growing exponentially in quickly developing digital age. The demand for more storage space has grown as more areas of life, from social media interactions to business transactions, are becoming digitalized. This article looks at how inadequate present storage capabilities are for keeping up with the rate of expansion in digital data and the significance of finding a solution.

- ***A Partial Solution:*** The increased need for storage space has a partial solution in the form of cloud storage. Cloud service providers can offer scalable storage options to consumers and businesses by utilising the enormous capabilities of data centres. This method, however, has its own set of drawbacks, such as worries about data privacy, security lapses, and dependence on outside sources [9]. Additionally, the cost of storing

significant amounts of data on the cloud can rise significantly, particularly for long-term retention.

- ***Explosive Growth of Digital Data:*** The internet's rising use, the widespread use of smartphones, and the rise of connected gadgets have all contributed to the digital revolution's data explosion. The amount of digital data is always growing because of all online interactions, transactions, sensor readings, and media uploads.
- ***New Technologies for Data-Intensive Systems:*** The problem with storage is made worse by the emergence of data-intensive technologies like *artificial intelligence, machine learning* , and big data analytics. Massive datasets are needed for these applications in order to build models and gain insightful knowledge. Additionally, the growing use of virtual reality, augmented reality, and high-definition multimedia content puts extra pressure on storage infrastructure by necessitating higher capacity and quicker data retrieval.

The lack of storage capacity is becoming an urgent issue as the digital world develops. Finding scalable and effective storage solutions is urgent given the exponential growth of digital data and the rising demand for data-intensive applications. While cloud storage provides a partial solution, research into next-generation storage systems is necessary to make sure that the storage infrastructure can sustain the ever-growing digital world [11]. It can fulfil the increasing need for storage space and unleash every advantage of the digital age by making investments in technology development and promoting innovation.

The problem of redundant information has grown significantly in importance in the era of expanding digital data. Traditional storage solutions frequently do not have built-in duplicate data management tools. The significance of data deduplication in eliminating redundant data and lowering storage costs is highlighted in this article.

Duplicate data refers to information that is identical and spread across different locations in a storage system. It may be caused by a number of things, including user error, system backups, or data replication procedures [13]. Duplicate data not only takes up valuable storage space, but it also drives up prices, slows down data retrieval, and uses resources inefficiently. Hard disc drives (HDDs) and solid-state drives (SSDs), two common types of traditional storage, lack built-in techniques for locating and removing duplicate data. Organisations can considerably reduce their storage needs by getting rid of duplicate data. However, ensuring that only one copy of each piece of information is stored, data deduplication increases data efficiency. Enhancing data integrity means reducing duplicate data [14]. Duplicate data can cause conflicts and inconsistencies, jeopardising the accuracy and dependability of data that is kept. Disaster recovery procedures might be hampered by duplicate data since it increases backup and restore times. In today's data-driven world, adopting data de-duplication is essential for effectively managing and maximising the value of digital data.

1.3Literature Survey

S. Luo and M. Hou in (2013) [24] offer a fresh approach to the chunk coalescing algorithm (CCA), which determines the most basic and highest amount of subchunks that must merge to create super chunks (SC). According to research, strategies speeds data decoding in general and lowers expenses related to the chunk coalescing (CC) process. The use of audiovisual data in a variety of uses in past decades has led to problems with analytics, security, sharing, and optimization. This review of the publications summarizes the results of four important studies on the subject, with an emphasis on data analytics, security models, safe multimedia data processing, and optimization methodologies in various contexts.

Krishnaprasad and B. A. Narayamparambil in (2013) [23] suggested a novel Dual Side Fixed Size Chunking (DSFSC) algorithm to achieve a rising de-duplication ratio for comparison to conventional FSC. Using this approach, the utilization of audio and video files to produce best De-duplication ratio without requiring variable space to chunk or content to be chunk. Storage management and energy expenses will be reduced if the request for storage use is reduced.

W. leesakul et al. in (2014) [22] suggested dynamic data de-duplication (DD) strategy for cloud storage, in order to strike a balance among changing storage efficacy and criteria for fault tolerance, as well as to increase cloud storage performance. adjust the number of copies of files in real time to match the changing degree of QoS. The results of the experiments reveal that suggested scheme works effectively and can deal with scalability issues.

R. Kiruba karan et al. in (2015) [18] present a cloud-based technique for achieving de-duplication of a huge amount of data available. The approach includes data de-duplication before uploading to cloud storage as well as data reverse de-duplication when obtaining the required data. The model is more effective and accurate than existing de-duplication systems because of the type of algorithm utilized.

V. Maruti et al. in (2015) [19] the main goal of this technique is to delete reiterate data from the cloud. It can also aid in the reduction of bandwidth and storage space usage. Each user has their own unique token and has been allocated various privileges based on the duplication check. The hybrid cloud architecture is used to achieve cloud de-duplication. The proposed technique is more secure and uses fewer cloud resources. It was also demonstrated that, when compared to the standard De-duplication technique, the proposed system had a low overhead in duplicate removal. On this work, both content level and file level de-duplication of file data is examined in the cloud.

X. Xu and Q. Tu, in (2015) [20] de-duplication scheme architecture for cloud storage environments (CSE). DelayDedupe, a delayed target de-duplication strategy rely on chunk-level de-duplication and chunk access frequency, is suggested to decrease response time in storage nodes (S nodes). When used in conjunction with replica arrangement, this technique evaluates whether fresh multiplied chunks for data update are hot and, if they aren't, eliminates the hot duplicated chucks. The findings of the experiment show that the DelayDedupe method may successfully minimize response time while also balancing the storage demand on Nodes.

Y. Zhang in (2015) [21] Suggested a novel CDC algorithm indicated the Asymmetric Extremum (AE) algorithm. The major idea behind AE is relies the observance that in dealing with the boundaries-shift issue, the maximum value in an asymmetric local domain is improbable to be exchanged through a novel extreme value, which motivates AEs utilize of asymmetric (instead of symmetric, as in MAXP) local domain to distinguish cut-points and attain high chunking throughput while minimizing chunk size variance. According to the result, AE addresses the issues of low chunking throughput in MAXP and Rabin, as well as excessive chunk-size volatility in Rabin, at the same time. AE enhances the throughput speed of state-of-the-art CDC algorithms by 3x while achieving equivalent or greater de-duplication efficacy, according to experimental results that rely on four real-world datasets.

W. Xia et al. in (2016) [16] suggest FastCDC, a Fast and effective CDC approach, which constructs and enhances on the latest Gear-based on CDC technique, one of the fastest CDC techniques to knowledge. Fast CDC’s main idea is to integrate five key mechanics: gear-rely on rapid rolling hash, improving and simplifying Gear hash (GH) verdict, skipping sub-minimal chunk cut-points, normalizing the chunk-size distribution in a small specific region to address the issue of reduction de-duplication

ratio caused by cut-point skipping. FastCDC is around 10 times quicker than the best open- source Rabin-based on CDC, and about 3 times greater than the state-of-the-art Gear- and AE-rely on CDC, while obtaining almost the same de-duplication ratio as the standard Rabin-rely solution, according to evaluation results.

X. Xu. et al. in (2016) [17] focus on non-center cloud storage data de-duplication and present a new two-side data de-duplication (DD) mechanism. The Chord algorithm (CA) is optimized. The suggested two-side data de-duplication (DD) technique outperforms the traditional data de-duplication (DD) mechanism in terms of de-duplication rate.

H. Wu. In (2018) [14] suggests a sampling-rely on chunking algorithm and improve SmartChunker, a tool to predict the appropriate chunking configuration for de-duplication schemes. Smart Chunk's effectiveness and efficacy have been demonstrated in real-world datasets.

M. Oh et al., in (2018) [15] suggest novel de-duplication technique that is extremely compatible and scalable with the exhausted storage currently in use. The approach combines file system and de-duplication meta-information into a single object, and it manages the de-duplication ratio online through initial aware of post-processing-related scheme demands. When executing a variety of standard storage workloads, the experimental findings illustrate that solution could save greater than 90% of total storage space while providing the same or similar performance as traditional scale-out storage.

N. Kumar and S. Jain in (2019) [11] suggest Differential Evolution DE-rely on TTTD-P optimized chunking to maximize chunking throughput while increasing de-duplication ratio DR The use of a scalable bucket indexing strategy minimizes the time it takes to find and declare duplicated hash values (HV). It chunks about 16

times greater than Rabin CDC, 5 times greater than AE CDC, and 1.6 times greater than FAST CDC (HDFS).

Y. Fan et al., in (2019) [12] system improves the capacity of like cryptosystems to resist selected plaintext and selection ciphertext attacks by augmenting convergent encryption with users' privileges and relying on TEE to provide secure key management. system is secured sufficient to facilitate data de-duplication (DD) as well as protecting the privacy of sensitive data, according to a security analysis. Moreover, create a prototype of system and analyze its performance. Experiments reveal that system overhead is practical in real-world scenarios.

H. A. Jasim and A. A. Fahad, in (2018) [13] novel fingerprint function (FF), a multi-level hashing and matching mechanism, and a novel indexing technicality to hold metadata to progress the TTTD chunking algorithm. These novel technicalities include four hashing algorithms to handle the collision issue, as well as adding a novel chunk stipulation to the TTTD chunking criterion to improve the number of small chunks and hence the De-duplication Ratio.

Xu and W. Zhang in (2021) [10] QuickCDC improves CDC chunking speed, de-duplication ratio, and throughput by combining three methods. Initially, QuickCDC can move instantly to the chunk boundaries of duplicate chunks that arise frequently. The mapping of the duplicate chunk's first n bytes and last m bytes to chunk length must be registered. The first n bytes and last m bytes of the current chunk are checked to see if they are in the mapping table when chunking is performed. QuickCDC can skip relevant chunk lengths (CL) if they are in the mapping table. QuickCDC can skip the minimal chunk length for unique chunks. Finally, QuickCDC may dynamically alter mask bits length such that chunk length (CL) is permanently more than the minimal chunk length and is distributed in a limited particular location. When the current chunk length (CL) is less than the expected chunk length (CL),

should use longer mask bits, and when the current chunk length (CL) is more than the expected chunk length (CL), should utilize shorter mask bits. Experiments show that QuickCDC's chunking speed is 11.4x that of RapidCDC, and the associated de-duplication ratio is somewhat increased, with a maximum de-duplication ratio improvement of 222.3% and a throughput improvement of 111.4%.

K. Vijayalakshmi and V. Jayalakshmi in (2021) [7] suggest data duplication in clouds, which is managed using the de-duplication technique. Although some de-duplication techniques are used to prevent data redundancy, they are inefficient. The major goal of this research is to gain enough knowledge and a decent concept of de-duplication techniques through reviewing existent ways, and this work may aid future research in establishing effective cloud storage management (CSM) solutions for researchers.

M. Ellappan and S. Abirami in (2021) [8] suggest a novel chunking algorithm called Dynamic Prime Chunking (DPC). DPC's major purpose is to modify the window size during the prime value dynamically rely on the maximum and minimal chunk size. DPC in the de-duplication scheme gives good throughput while avoiding large chunk variance. The multimedia and operating system datasets were used for implementation and experimental evaluation. Existing algorithms such as AE, MAXP, TTTD, and Rabin have been compared to DPC. The performance indicators looked at were throughput, chunk count, Bytes Saved per Second (BSPS), chunking time, processing time and De-duplication removal Ratio (DER). BSPS and throughput have both improved. To begin, DPC boosts throughput performance by greater than 21% when compared to AE. BSPS improves performance by up to 11% over the previous AE method.

P.Anitha et al. in (2021) [9] the secure authorities are given access control mechanisms to do data de-duplication (DD) on the data that was outsourced.

Encryption techniques are used in the Access Control Mechanism. It employs convergent randomised encryption and a reliable distribution of owning party keys to allow the cloud service provider to manage outsourced data access even when control shifts on a regular basis. The suggested technique safeguards data integrity against attacks relies on label discrepancies. As a precaution, the suggested technique has been changed to improve security.

In the year 2023, Dhar et al. proposed a very advanced and safe Security Model for Multi-media Data or info Sharing (sending and receiving) in the Internet of Things (IoT) context. However, methodology offers a comprehensive approach to secure multimedia data flow in IoT ecosystems, that Internet of Things devices are vulnerable to security breaches. Authentication, and encryption technologies in an attempt to lower and minimize the risks linked with unauthorized access and data breaches, for this purpose this study integrates access control. This research emphasizes how robust security frameworks are essential to ensure the unique and unknown challenges posed by sharing visual data in Internet of Things environments.

In the year of 2022, Srinivasan et al. technique for medical purpose supply. They focus on the important requirement for security when handling such sensitive cases of medical info by proposing a method that ensures secure processing of multi-media data. Encryption and access controls to safeguard patient privacy and stop unauthorized access to medical records this approach is recommended for easy and safe use. This analysis shows how crucial is security measures are to just maintain data integrity and also confidentiality in medical applications or processes Kumari and Tanwar in the year of (2022) provided a secure and very safe trusted data analytics method intended for multi-media communication in a decentralized smart grid architecture that is very useful. Therefore, decentralized environments

preserving data analytics processes their proposal addresses the challenge with a focus on the energy industry. Further, with the combination of anomaly detection, encryption, and authentication processes that enhances the security of multimedia information analysis and transmission in smart grid networks. This knowledge highlights the importance of safe data and information analytics in ensuring the dependability and integrity of critical infrastructure systems.

The primary objective of Sharma et al. in the year of (2023) work on to maximize multi-media information through computationally intelligent algorithms. Therefore, their research and study examines the potential applications of the most worldwide common and known artificial intelligence techniques to enhance the performance and usefulness of multimedia systems. Hence, this proposed problem uses intelligent methods such as machine learning and optimization algorithms just to optimize multi-media information processing, storage, and retrieval. This study and research illustrate how computational intelligence can be applied to address the difficulties or circumstances linked with managing multimedia data and enhance system efficiency.

The majority of the assessed studies highlight how crucial security, data analytics, and optimization strategies are while managing multimedia data in a variety of industries. These studies assist in the field of multimedia tools and applications by providing insightful knowledge and useful techniques for tackling the difficulties involved in the safe processing, distribution, and optimization of multimedia data.

Table 1.1: Comparison between studies over Data De-duplication & chunking algorithm

S. No.	Authors	Algorithm/method/ Techniques	Advantages	Drawback

1	N. Kumar and S. Jain 2019	Differential Evolution (DE), Two Thresholds Two Divisors (TTTD-P) algorithm,	Hash values (chunks about 16 times greater than Rabin CDC, 5 times greater than AE CDC, and (1.6) times greater than FAST CDC	Take too much time to calculate the hash value.
2	W. Leesakul et al. 2014	Dynamic Data De-duplication	experiments reveal that our proposed system works effectively	Cannot work with the encryption keys
3	Y. Fan et al. 2019	De-duplication system that includes the processes of duplicate checking	implement the security analysis and also performance evaluation is effective and feasible in practice	Take too much processing power of the system and consume more power
4	M. Oh et al. 2018	A novel de-duplication technique	experimental findings illustrate that our solution could save greater than 90% of total storage space	It will occupy more than 20% more storage than other algorithms
5	P. Anitha et al. 2021	secure rising scalable data de-duplication architecture	The system is virtually as successful as the existing ones (minor increase	Risk factors high

			in computational overhead)	
6	R. Kiruba karan et al 2015	a cloud-rely technique for de-duplication of huge data	The model is more efficient and accurate compared to that of the existent de-duplication techniques.	The model is efficient but it is too expensive.
7	M. V. Maruti et al. 2015	novel duplication check technique that configuration the token for the private file	the system achieve is 98 %	Consume more power for execution
8	K. Vijayalakshmi and V. Jayalakshmi 2021	data duplication (DD) in clouds	the system achieves efficient knowledge and a good idea concerning de-duplication techniques	Can not manage TB of data in the cloud environment
9	X. Xu et al 2016	two- side data de-duplication (DD) technique, Chord algorithm	two-side data de-duplication (DD) technique outperforms the traditional data de-duplication technique in terms of de-duplication rate	Can not manage more than 50 VMs

10	X. Xu and Q. Tu 2015	de-duplication scheme architecture for cloud storage environments (CSE)	Delay Dedupe method may successfully minimize response time while also balancing the storage demand on Snodes	algorithms often lack comprehensive validation and may not be well-understood by the research or practitioner communities
11	M. Ellappan and S. Abirami 2021	Dynamic Prime Chunking (DPC), Existing algorithms,	DPC's durable performance over the another existent algorithms in terms of BSPS and the efficacy of the backup storage scheme	Storage and cost high
12	H. A. Jasim and A. A. Fahad 2018	a novel fingerprint function (FF),	good de-duplication ratio and rapid execution time, efficacy of the suggest algorithm was evaluated utilizing two relatively datasets	Efficiency increases but attack rate is high

13	W. Xia et al., 2016	FastCDC, a Fast and effective CDC approach	FastCDC is around 10 times quicker than the best open-source Rabin- based on CDC, and about 3 times greater than the state-of-the-art Gear- and	Algorithms in terms of Chunk and the efficacy of the backup storage is less
14	Z. Xu and W. Zhang 2021	Content Defined Chunking (CDC)	Show that QuickCDC's chunking speed is 11.4x that of RapidCDC, and the associated de-duplication ratio is somewhat increased, with a maximum de-duplication ratio improvement of 222.3%	drawback of the Content-Defined Chunking (CDC) algorithm is its potential sensitivity to changes in data patterns.
15	S. Luo and M. Hou 2013	a new chunk coalescing. algorithm (CCA)	demonstrate that our algorithm eliminates the expenses of the chunk coalescing procedure and enhance the efficacy of hash-comparison	CCA may not perform optimally across all types of data or workloads. It is primarily designed to reduce redundancy in

				similar chunks, so it may not be as effective for datasets.
16	H. Wu et al. 2018	a sampling-based on chunking algorithm and improve SmartChunker	illustrate that a sampling-based chunking algorithm and enhance SmartChunker application-specified chunk configurations	The algorithm's efficiency can be compromised if the chosen sampling strategy introduces bias, leading to suboptimal chunk boundaries and reduced effectiveness

1.4 Research Problem

The Internet of Things' (IoT) explosive growth has completely changed how data is created, shared, and used, opening up previously unheard-of possibilities for efficiency and creativity in a wide range of industries. Nonetheless, a number of difficulties have emerged as a result of the smooth integration of IoT devices with cloud computing platforms, mainly in relation to the administration and storage of enormous amounts of data produced by IoT devices. Under this situation, the creation of a trusted and safe data storage system specifically designed for cloud-based Internet of Things applications is the urgent research challenge. There are several challenges facing data storage in these types of contexts today, from privacy and data security issues to process efficiency for storage and retrieval.

Ensuring the privacy and security of Internet of Things data while it is stored in the cloud is the most crucial consideration. Since, a significant quantity of this information is very sensitive—that is, because it contains private and personal information—severe security measures must be implemented to guard against hostile attacks, illegal access of unknown to data and privacy, and data breaches. Furthermore, for making security obligations more complicated legal frameworks such as GDPR and HIPAA makes data security obligations possible that no one can access easily. In addition, in cloud-based Internet of Things system, there are numerous challenges concerning the scalability and accessibility of data storage options. Due to the growing number of IoT devices the data volume has increased exponentially, making it challenging for standard storage systems to meet the requirements and needs for scalability and efficiency. Consequently, the development of innovative solutions that can highly available and dependable scale storage resources in response to changing workloads is essential. To improve and make better the system's overall effectiveness and performance, it is also important to optimize the retrieval and storage techniques and methods. IoT-generated data can range widely and vast, from multi-media content to real-time detectors readings, therefore, storage mechanism designs need to be adaptable enough to accommodate various data kinds and access patterns. Hence, data retrieval algorithms specifically designed for cloud-based IoT systems, data storage architectures and includes researching state-of-the-art info indexing methods. To confront these intricate challenges, a holistic approach by the combination technological innovation, robust security protocols, regulatory adherence, and also efficient resource allocation is needed. We can make possible due to the most of IoT technology while lowering and minimizing associated risks and ensuring the security and integrity of sensitive data or personal data by developing a very safe, trusted and effective data storage

system for cloud-based Internet of Things applications. This project of research will open the door to a more resilient, secure or safe, and networked digital world by significantly influencing that how the cloud computing and Internet of Things ecosystems evolve in the future.

1.5 Research Objectives

The goal of this research is to create a new, effective system for Internet of Things and cloud storage environments. The suggested method is intended to attract interest in massive text, picture, and video storage systems. Therefore, in order to fulfill the research goal, the following criteria are developed:

1) For designing a mechanism just to improve the performance of a large storage system by only applying the de-duplication technique or method.

2) To assess how effectively the suggested mechanism performs in a simulated setting in contrast to existing solution.

3) To confirm and verify the suggested approach using the findings from simulation studies to guarantee that it's application is correct.

1.6 Contribution of the Research

Middleware is another piece of software that the central server uses to allow the networked machines to communicate with each other.

1) Mechanism Design: The study suggests a method for cloud storage in internet of things settings, focusing performance improvement via the use of deduplications strategies. This strategy attempts to solve a major issue in large-scale storage systems by optimizing resource use and lowering the cost of storage.

2) Performance Evaluation: In simulated scenarios the research does through performance evaluations of the suggested mechanism in comparison to current solutions. Through an in-depth assessment of its effectiveness scalability and also reliability, the study offers insightful information on how well the suggested approach works in practical applications.

3) Validation and Verification: By means of meticulous validation and verification procedures grounded in simulation tests, the study guarantees the accuracy and efficacy of the suggested method. Through functional and performance verification against pre-established benchmarks, the study validates the suggested solution's viability and reliability and realistic implementation in cloud-based IoT systems.

1.7 significance of the research

By improving security and privacy protections within the suggested mechanism, the research directly addresses Objective. The successful resolution of the challenge surrounding an efficient secured data storage method for cloud-based IoT promises to bring about a plethora of crucial. Achieving heightened security ensures the protection of IoT-generated data stored in the cloud, aligning with the objective to design a mechanism to improve large storage system performance through deduplication techniques. As the proposed mechanism ensures secure and efficient data storage, it directly contributes to instilling greater confidence in the utilization of IoT technologies, supporting Objective. Organizations and individuals will trust IoT applications more knowing their data is securely stored, thereby validating the mechanism's performance in comparison with existing solutions. The enhanced accessibility and reliability of IoT data resulting from the proposed mechanism directly support Objective through verification and validation processes, the research confirms the correctness and effectiveness of the mechanism, ensuring its reliability in storing and retrieving data seamlessly. Efficient resource utilization, including cost and energy savings, is a direct outcome of the proposed mechanism, in line with Objective by optimizing storage efficiency through deduplication techniques, the mechanism minimizes resource wastage, contributing to the performance improvement of large-scale storage systems. The proposed mechanism's ability to seamlessly scale to accommodate increasing volumes of IoT data aligns with

Objective through simulation experiments and performance evaluations, the research verifies the mechanism's scalability, ensuring its suitability for evolving IoT deployments without storage limitations.

1.8 Outlines of Thesis

The following chapters are presented in this thesis: Chapter One presents the basic introduction, problem statement, methodology objective of the study and some other aspects. Chapter Two presents the theoretical background. It theoretically explains the method and techniques used in this study. The proposed methods or methodology used in this study will be depicted in Chapter Three. The collected methods, techniques, algorithms collected in the proposed methodology will be analyzed in this chapter. The primary outcomes of the proposed system employing various strategies are shown in Chapter Four. The findings are given separately for each model. Chapter Five summarises the results reached throughout this thesis, overall conclusion derives from the study and briefly lists potential future works.

Chapter Two

Theoretical Background

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2.1 Performance Metrics and its Types:

Cloud storage in IoT setup has become essential for data management in daily based linked society. However, the performance of this data storage is just important for implementation success. IoT context have examined the verities in term of efficiency measure.

1. Throughput: In this way the transmitted and received data retrieved from cloud storage system. For fast analysis and processing in IoT environments, throughput matrices assess the system's ability for leading smooth operations and insights.

2. Latency: Latency is also known as lag of between data reception and transmission and to know how much effective is the IoT apps are. Low latency is used to require instantaneous data processing such as real time controlling and monitoring. IoT functions as efficiently and with the least amount of latency possibility.

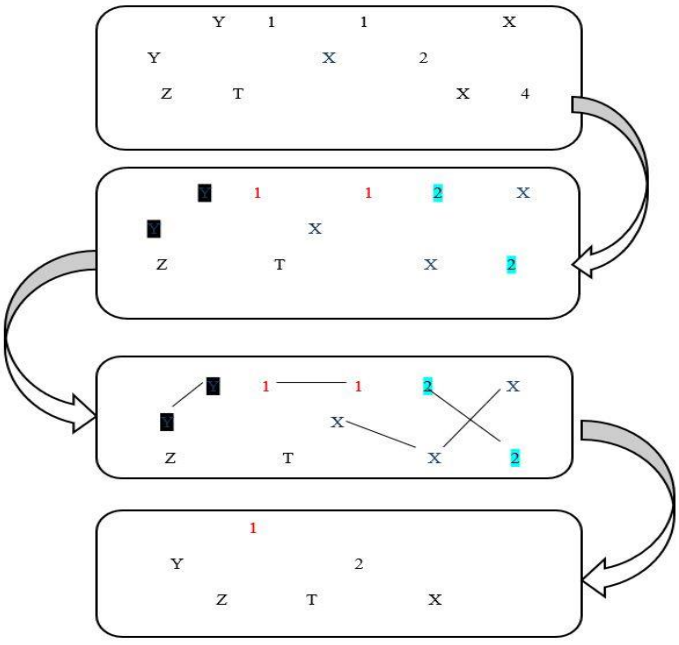
3. Availability: This shows how easy it is to access the data stored in the cloud. High availability is needed to ensure continuous access to relevant information in the context of the Internet of Things, where data accessibility is crucial for decision making and operations. To sustain the continuous availability of data and to avoid interruptions, Availability metrics look at the reliability of cloud storage infrastructure which includes backup and redundancy systems.

4. Scalability: Scalability matrices measure the performance and resources usage as data over time alter. Scalable solutions are more important because of the needs in dynamic IoT environments where quantities might change quickly.

5. Reliability: Reliability is used for measuring the capacity of cloud storage and its performance in the prediction manner over the passage of time. IoT is consistent and reliable storage solution that maintain the data integration.

2.2 Data Deduplication

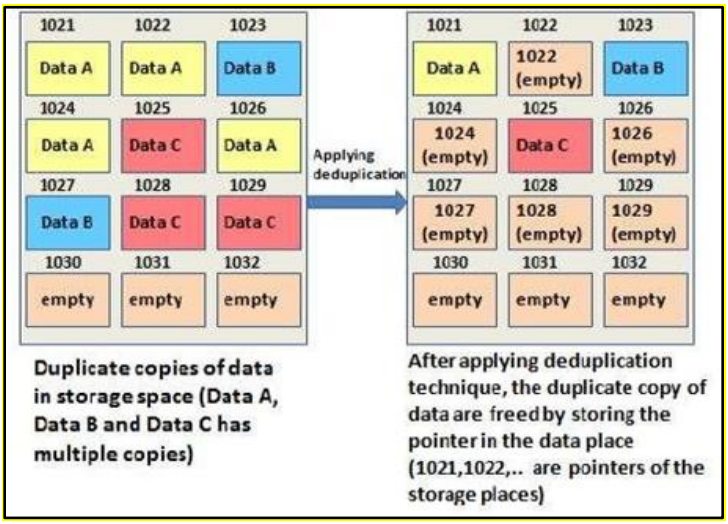
Across several cloud storage system data duplication is the existence of redundant data and IoT devices. As the operation of cloud based IoT systems the optimization storage resources and computations speeds is essential to solve the problem. In order to effectively identify and delete duplicate data, sophisticated algorithms and techniques are used in cloud IoT systems [25]. Proliferation of IoT devices and also managing their effectively is crucial task. De duplication method like indexing metadata and hash based comparisons can be used to save network and bandwidth spaces. Data duplication can be enhanced by data analysis and decision-making, promotes data security and privacy compliance, and enables the seamless integration of IoT technologies in various industries and applications [26].



(a) Fig: 2.1 Data Duplication [78]

Data duplication like identifying and vanishing redundant samples of the data can be shown in the data duplication graphics. It entails operations such as

segmenting the data into digestible chunks, identifying unique chunks, and substituting references to the unique chunks for superfluous ones. Below graphs also illustrate that how data deduplication improves efficiency of storage and transport of networks by transferring and storing.



(b) Fig: 2.1 Data Duplication [79]

Data duplication figure also find out many techniques and ways for large scale storage system. It provides examples of chunking, indexing, hashing, and algorithms for identifying duplication. It also analyses that how techniques are stored overhead and boosted in cloud system.

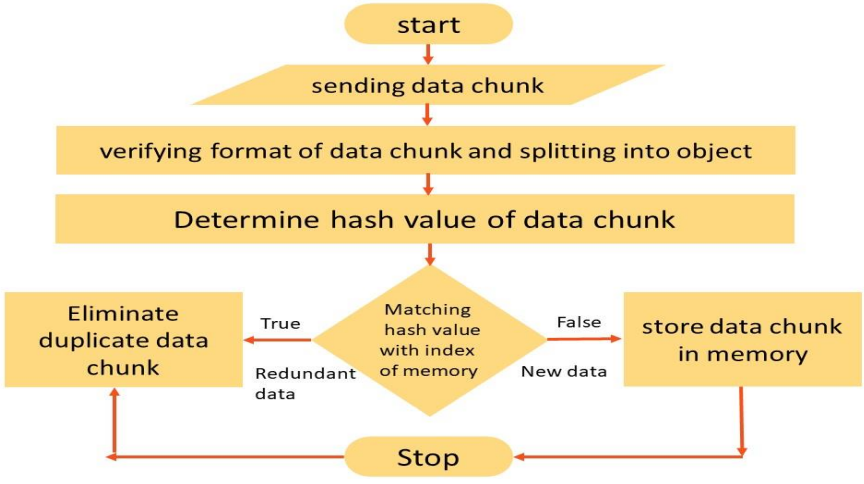


Figure 2.1: (a, b & c): Data De-duplication [28]

Following are the hashing algorithms and techniques in the context of IoT and cloud storage.

SHA-256 (Secure Hash Algorithm 256): Widely used for its robustness and security, SHA-256 generates a fixed-size 256-bit (32-byte) hash. In IoT applications, SHA-256 can be employed to securely hash sensitive data before transmission to the cloud for storage. This ensures data integrity and confidentiality.

MD5 (Message Digest Algorithm 5): While less secure than SHA-256 due to vulnerabilities, MD5 is still utilized in certain IoT systems for its simplicity and speed. However, its usage is diminishing in favor of more secure alternatives due to collision vulnerabilities.

HMAC (Hash-based Message Authentication Code): HMAC combines a cryptographic hash function (such as SHA-256) with a secret key to provide data integrity and authenticity. In IoT scenarios, HMAC can be applied to verify the integrity of data exchanged between IoT devices and cloud storage, preventing tampering or unauthorized access.

Salted Hashing: This technique involves adding a random value (salt) to the input before hashing, enhancing security by mitigating precomputed hash attacks. IoT devices can utilize salted hashing when storing sensitive credentials or personal information in the cloud, making it more challenging for attackers to reverse-engineer the original data.

Bloom Filters: While not a traditional hashing algorithm, Bloom filters are probabilistic data structures used to efficiently test whether an element is a member of a set. In IoT applications, Bloom filters can assist in reducing the computational overhead of searching for specific data items stored in the cloud, thereby optimizing resource utilization in resource-constrained IoT environments.

These examples illustrate how various hashing algorithms and techniques can be leveraged to enhance security, integrity, and efficiency in IoT-cloud storage systems. Figure 2.1: (a) representing data entry into system, (b) subsequent phases, like chunking, hashing, and duplicate detection, (c) Deduplication Process.

DE duplicated illustrates the process of storing unique data together with potential metadata or links. This diagram makes the procedure for decreasing redundant data and increasing storage efficiency in the deduplication system more understandable.

A deduplication flowchart is typically used to analyse the identification and elimination of duplicate data inside a system. After entering the data into the flowchart, a comparison process is applied. In this step, the data is analyzed to look for duplicate items. When a judgment point is reached in the case that duplicates are found, redundant data is eliminated. After deduplication, the flowchart can advise storing the cleaned data in a database or another kind of storage system. This process maximizes storage capacity, improves data accuracy, and raises overall system efficiency by making sure that only unique and non-redundant data is retained. Through the visual representation of these stages, a deduplication flowchart offers a clear and systematic overview of the data cleaning process, aiding in understanding and execution for a range of applications, including databases and cloud storage [27].

The process known as data de-duplication, or just Dedup, lowers the cost associated with storing duplicate data. Data De-duplication maximizes the amount of free space on the volume by examining the data and looking for portions that are duplicated. Duplicate sections of the dataset are only stored once and can be compacted to save space if needed. Data de-duplication reduces redundancy while maintaining data authenticity and integrity. Data de-duplication is a process that gets rid of duplicate data and drastically lowers the amount of storage space needed. De-duplication can be carried out as a background process to get rid of duplicates after data has been

recorded on disk, or it can be done as an inline procedure as data is written into the storage system. Since de-duplication operations operate in a different efficiency domain from the client read/write domain, their performances are minimal. Regardless of the application that is open or the method used to access the data (NAS or SAN), it operates in the background. When data moves between on-premises, hybrid clouds, and/or public clouds, or is duplicated to a disaster recovery site or backed up to a vault, de-duplication savings are maintained. Chunking is the process of breaking up a stream of data into many segments. Although there is a reduction in computing cost when the chunk size is large, the effect of deduplication might not be noticeable right away. When the chunk size is very small, computation is expensive, and deduplication has a discernible effect.

2.2.1 Methods of Data Deduplication

The data gathered through various sources and the emergence of the IoT has significantly increased the volume of data from petabytes to yottabytes, therefore necessitating the cloud computing paradigm in order to process and store data. The duplicated sections of the dataset are stored once along with being subjected to optional compression to free up even more space. It is also beneficial in ensuring veracity along with maintaining data integrity. [43] There are various methods of data deduplication such as inline deduplication, post processing duplication, source deduplication, target deduplication and client-side deduplication. There are two approaches that may be used to remove unnecessary deduplicate from material. [44]

1) **Deduplication In-Line.**

Due to the fact that it is processed inside a reinforcement framework, inline deduplication simplifies the information. When information is maintained in contact with reinforcement accumulating, it is possible to eliminate instances of duplication. Although inline deduplication needs less stockpiling of reinforcements, it might still

result in bottlenecks. The capacity exhibit provider recommends that their inline data deduplication solutions have their output twisted off in order to achieve high throughput.

Inline deduplication is a widely prevalent method that comprises deduplication and compression where data reduction takes place before the incoming data is written to the stored media. Inline deduplication is essentially the removal of redundancies from a given data along with being a software defined storage solution or a storage controller that is in control of the places and the processes through which the data is saved and secured. The Inline deduplication method takes account of the entirety of data going through the tool and is scanned, deduplicated and compressed in real-time. Additionally, inline processing is also found to reduce the raw disk capacity that is needed in the system.

It takes place because the un-deduplicated and uncompressed dataset in its original size is never written to the disk. Therefore, the write operations that are executed are also comparatively lower thereby reducing the wear on the disks. However, it can also be observed that in inline deduplication the process significantly slows down the data backups that eventually is found to impede the entire process. This eventually reflects the fact that the result will thereby be devoid of any redundant or inefficient data. Inline deduplication is found to rely on the processes that exist between the data origin servers and the data backup destinations.

2) De-duplication After Processing

Simultaneously, post-processing data duplication is the process where the data at first is written to the storage media which is then followed by the analysis of duplication along with identification of any scopes for compression opportunities. The deduplication and compression is executed only after the data is securely stored in the storage device. In addition to this, in the process of post-processing data

duplication the initial capacity that is required is somewhat related to the raw data size. Simultaneously, the optimised data is then saved back to storage media. It is done with relatively lesser space requirements in comparison to that of before data reduction.

Post-processing dedupe is a 735 synchronous reinforcement operation that eliminates repeated data after it has been maintained in contact with capacity. The data that has been entered more than once is removed, and it is replaced with an indication that is positioned toward the principal focus of the square. The post-processing method provides customers with the flexibility to dedupe certain remaining jobs at hand and the speed to quickly recoup the most recent reinforcement without requiring water. The trade-off for this is a larger reinforcement stockpile limit than would be required with inline deduplication [45]. Post-processing data duplication is identified as an asynchronous backup process that is beneficial in the removal of redundant data after it is successfully written to storage. This process provides the user with enough flexibility and independence towards deduping specific workloads along with efficient recovery of the most recent backup. The post-processing data duplication is found to utilise the latest backup and is therefore found to take up more disk space in comparison to other deduplication processes. However, the post-processing data duplication takes a relatively lengthier processing time because of the fact that data is identified prior to the removal of the duplicate data from the storage unit.

3) Source Deduplication

When data deduplication is applied at the source of data generation or transmission, it is referred to as client-side deduplication. Data deduplication processes are carried out on the client or source device prior to the data being transferred over the network to the storage destination, like a cloud server or backup appliance. This method

entails locating duplicate data blocks or chunks within the data stream at the source device and removing redundant copies before the data is transmitted to the storage system. By removing duplicate data at the source, source deduplication reduces the amount of data transferred over the network and stored on the destination storage system, resulting in significant savings in bandwidth and storage capacity.

4) Target Deduplication

Target deduplication is a type of data deduplication where the data is processed at the target device, like a storage array or backup appliance, or at the storage destination. Target deduplication finds and removes redundant data after it has been transferred and stored on the destination storage system, as opposed to source deduplication, which does so at the source before transmission.

Target deduplication involves data deduplication operations carried out on the storage device itself. Here, redundant data blocks are found and removed using preset patterns or algorithms. With this method, businesses may reap the benefits of data reduction and storage optimization without having to modify their client or source devices.

2.2.2 Data Deduplication strategies

Primarily, there is the record level, the square level, and the byte-level method, and each of them may be improved for increased storage capacity.

- File-level data deduplication strategy: This strategy functions at the file level and not at the sub-file level or the block level. File-level data deduplication is a technique used for data optimization. This helps in eliminating redundancy at the file level. This is what helps this strategy significantly save storage space and improves the efficiency of data storage. This strategy first identifies the duplicate files and then retains only a single instance of each unique file. The duplicates are replaced as references and pointers to the original file. The

duplicate files are identified across the whole storage system. The duplicate files are identified regardless of their location or format.

This technique is particularly effective where the files are frequently duplicated. It is also effective in an environment where many similar files are stored. For example, it will be very effective to use a file-level data de-duplication strategy in file servers or data repositories [46]. The major benefit of file-level data de-duplication is that it helps in reducing storage space. In addition to that, this technique also helps to reduce backup windows, improving backup and restore performance. This involves only unique files, which makes the backup of files faster and reduces the recovery times of the files.

These benefits help to reduce the corruption of files as the number of files gets reduced. This definitely enhances the entire data management system. The two steps used in this technique include:

1. The system scans the storage environment, which includes analysing the metadata and the duplicate content files. Metadata contains details like names, sizes, creation dates, and more attributes of the file [47]. The Metadata helps to differentiate between two or more different files. The analysis of the content involves an actual data examination within the files.
2. The identification of the duplicate files is followed by keeping one single copy of the file as the reference file and the other duplicate files are saved as pointers or references to the primary file [48]. This gives easier access to duplicate files with the help of pointers and clearly saves storage space.

- Block-level data deduplication technology: This technique is different from

the file-level de-duplication technique as in this; the duplicate file is identified at the granular level. These are called “data blocks”. The data from different files are broken into blocks to identify duplicate data. The identified duplicate data is then replaced with pointers or references to the single instance of the block [49]. The three main benefits of this technique include saving storage space, reducing backup windows, and enhancing data transfer speeds. The data in this technique is stored in fixed or variable-sized blocks. The sizes of these blocks range between a few kilobytes to several megabytes.

Each block identified in this technique is processed individually and the unique hash value for each block is calculated. This hash value represents the data within each block and hence serves as a fingerprint for accessing the data. The significant steps in this data deduplication technique are:

1. The data from the files are broken into blocks after a thorough scanning of the files.
2. The hash values are assigned to each block, which helps in easy access to these data. This helps to find the duplicate data in these files.
3. The hash value brings forward the duplicate data and these are then replaced with pointers or references to the single block file. This block is called the *“reference file”.*

This technique helps in making the storage process efficient. Organisations can reduce storage space by eliminating the identified duplicate files. Organisations often use this method to store higher amounts of data in the same storage system. This technique also helps to have an efficient backup and restore system [50]. This happens because this technique only uses unique blocks and these are transferred and stored as it is. This makes the backup time lesser and creates shorter backup windows.

- **Block-Level Innovation**

Modifications made on the inside of the file will result in the whole document having to be stored. PPT and other documents may need to undergo minor adjustments to their fundamental information. For instance, if a page has to be updated to display the most recent report or the dates, this may need a complete restore of the archive. The block level information de-duplication technology saves just one version of the paper and the subsequent portion of the differences that have been made between versions. The file-level innovation, which is often under a 5:1 compression ratio, whereas the block-level storage innovation may pack the information limit of 20: 1 or even 50: 1

- **Evacuate File Level Innovation**

File-level information de-duplication technology, the record is extremely little, and the rehashing of the information by the designated authority takes practically no time to calculate. Because of this, the method for expulsion has very little impact on the execution of reinforcement. Due to the fact that the file is little and has a low recurrence level, the report level handling load needed to evacuate the innovation is also comparatively modest. A less impact on the amount of time required for recovery. Remove the technical need to "reassemble" the information square by using the square level essential file coordinating square and the information square pointer. The record level innovation consists of a one-of-a-kind archive storage and highlighting the document pointer, which significantly reduces the amount of time required to rebuild.

- **Cloud Storage Mechanism**

Every cloud has a certain amount of storage, so if start uploading duplicate information, the storage will be lost, and dealing with data redundancy will become a major issue. Researchers have been investigating numerous techniques to combat

this, and data deduplication is the best answer. A method called data deduplication was developed to improve storage [77]. Different cloud service providers, including Dropbox, Amazon S3 and Google Drive, now use this strategy. Data duplication is prevented by making sure it is never uploaded to the cloud more than once.

A. As the amount of digital data grows, so does the need for greater storage space.
B. Traditional solutions don't have any built-in protection against duplicate data being saved up.
C. Data De-duplication is critical for removing redundant data and lowering storage costs.

The quantity of data generated is growing exponentially in quickly developing digital age. The demand for more storage space has grown as more areas of life, from social media interactions to business transactions, are becoming digitalized. This article looks at how inadequate present storage capabilities are for keeping up with the rate of expansion in digital data and the significance of finding a solution.

- A Partial Solution: The increased need for storage space has a partial solution in the form of cloud storage. Cloud service providers can offer scalable storage options to consumers and businesses by utilising the enormous capabilities of data centres. This method, however, has its own set of drawbacks, such as worries about data privacy, security lapses, and dependence on outside sources [9]. Additionally, the cost of storing significant amounts of data on the cloud can rise significantly, particularly for long-term retention.
- Explosive Growth of Digital Data: The internet's rising use, the widespread use of smartphones, and the rise of connected gadgets have all contributed to the digital revolution's data explosion. The amount of digital data is always growing because of all online interactions, transactions, sensor readings, and media uploads.

- New Technologies for Data-Intensive Systems: The problem with storage is made worse by the emergence of data-intensive technologies like artificial intelligence (AI), machine learning (ML), and big data analytics. Massive datasets are needed for these applications in order to build models and gain insightful knowledge. Additionally, the growing use of virtual reality, augmented reality, and high-definition multimedia content puts extra pressure on storage infrastructure by necessitating higher capacity and quicker data retrieval.

The lack of storage capacity is becoming an urgent issue as the digital world develops. Finding scalable and effective storage solutions is urgent given the exponential growth of digital data and the rising demand for data-intensive applications. While cloud storage provides a partial solution, research into next-generation storage systems is necessary to make sure that the storage infrastructure can sustain the ever-growing digital world [11]. It can fulfil the increasing need for storage space and unleash every advantage of the digital age by making investments in technology development and promoting innovation.

The problem of redundant information has grown significantly in importance in the era of expanding digital data. Traditional storage solutions frequently do not have built-in duplicate data management tools. The significance of data deduplication in eliminating redundant data and lowering storage costs is highlighted in this article.

Duplicate data refers to information that is identical and spread across different locations in a storage system. It may be caused by a number of things, including user error, system backups, or data replication procedures [13]. Duplicate data not only takes up valuable storage space, but it also drives up prices, slows down data retrieval, and uses resources inefficiently.

Hard disc drives (HDDs) and solid-state drives (SSDs), two common types of traditional storage, lack built-in techniques for locating and removing duplicate data.

Organisations can considerably reduce their storage needs by getting rid of duplicate data. However, ensuring that only one copy of each piece of information is stored, data deduplication increases data efficiency. Enhancing data integrity means reducing duplicate data [14]. Duplicate data can cause conflicts and inconsistencies, jeopardising the accuracy and dependability of data that is kept. Disaster recovery procedures might be hampered by duplicate data since it increases backup and restore times. In today's data-driven world, adopting data de-duplication is essential for effectively managing and maximising the value of digital data.

2.2.3 Process of Data

A method known as "data deduplication" may be used to get rid of multiple copies of data that is repeated. You may also know it by the name Single Instance Storage. There are two distinct methods of deduplication, which are referred to respectively as deduplication at the file level and at the block level **[50].** While deduplication at the file level takes into consideration the whole file, deduplication at the block level applies deduplication to data blocks using hashing methods.

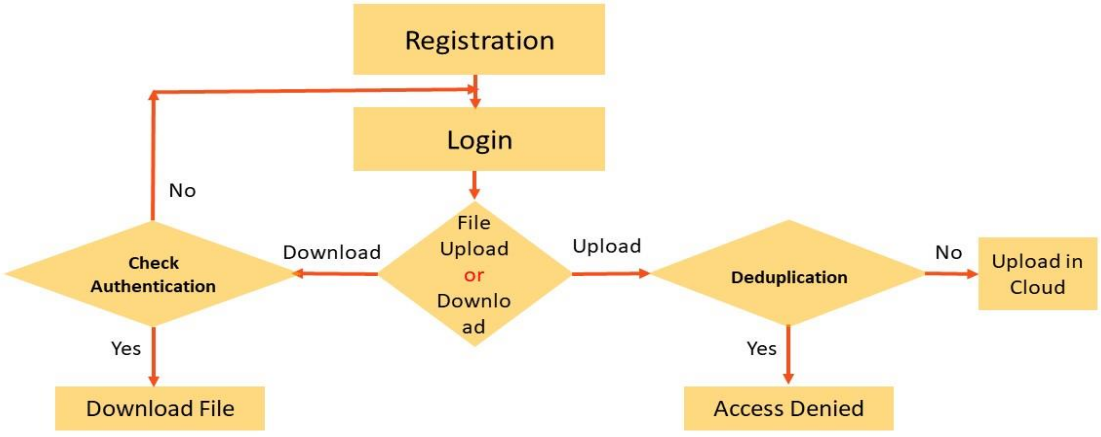


Figure 2.2: Deduplication Flowchart [51]

The figure 2.2 deduplication flowchart effectively displayed the process of data optimization through applying deduplication procedures. The procedure starts with the registration process from the end of users. Users provide various primary and

well-organised information about themselves or their organisations in order to register themselves into the cloud storage system. The successful registration takes them to the login page of the cloud storage system. The users are required to provide their login id and password in order to access their data stored in the database. The login id and password is used to ensure the safety and privacy of all the stored data.

However, if the registration process of the user fails then the user is asked to re authenticate their credentials and basic information. The successful login using the correct credentials take the users to the upload and download section. Downloads of the stored files require authentication from the system. Users can download the asked files if they are authenticated to do so. However, if the user wants to upload a file in the cloud storage then the duplication of the file will be checked. The access is denied if any kind of duplication is found on the provided file. Cloud storage systems grant the permission to upload any new file if no duplication is found on the provided file.

2.3 Purpose of Data Deduplication

It is crucial to eliminate duplicate data within a dataset for efficient management of data and save storage space. Therefore, it can be said that data De-duplication helps enhance the integrity of the data while improving the system's performance as well. In order to get an in-depth picture of the significance of data De-duplication, here are some key points explained in details:

1) **Optimization of System Storage:**

After reviewing other studies on this subject, it has been understood that not only duplicate data takes up unnecessary storage space, but also hampers the overall system performance. Data De-duplication identifies duplicate data and files in the device, and removes them to make space for other important data. Examples of data De-duplication in real world scenarios can be found in backup systems,

archives, and cloud storage. These services use data De-duplication to prevent data redundancy while improving the data retention capabilities of itself.

2) Bandwidth Conservation:

Bandwidth conservation becomes a key factor when data is to be transferred across domestic networks. It also becomes crucial while data backup to different locations (offsite). The Data Deduplication comes in use in this case selectively remove repetitive data prior to the transfer. This is done so that the data that is to be transferred is reduced in size, and only takes up space that is crucial for the core dataset. However, this also helps in faster transfer of the data, lower bandwidth needed for the transfer of data, and lesser network traffic.

3) Data Governance Regulations and compliance of them

Government has placed several strict regulatory compliance measures on companies and industries regarding data handling. In such cases, data deduplication comes into play by helping companies meet most of these regulations. Additionally, it also helps in "data tracking" efficiently, and helps to follow the data governance practices as prescribed.

4) Data integrity and Data loss:

Data De-duplication can improve the integrity of the data and confirm only one version of each data to exist in the data set It is important to avoid any sort of duplication of data as they can cause errors and inconsistencies. If in any circumstances, there is data loss, data de-duplication makes the data recovery process much simple. It also ensures that there are less risks of data corruption and faster process of system restore.

The expenditures that are connected with duplicated data may be reduced by storage managers with the assistance of data de-duplication. When dealing with large

datasets, it is common to find a significant amount of duplication, which drives up the cost of storage. As an example:

- It's possible that different users' file sharing includes several copies of the same or similar files.
- Virtualization guests may often be almost exactly the same from one VM to the next.
- There may be some variation from one day to the next in the backup snapshots.

The dataset or the workload on the volume will determine the amount of space that can be saved thanks to data de-duplication. High-duplication datasets have the potential to reach optimization rates of up to 95%, which would result in a 20-fold decrease in the amount of storage space required. The following table provides a summary of typical cost reductions that may be achieved by de-duplication of different categories of material:

Table 2.1: Data De-duplication Scenario & Typical space savings

Scenario	Content	Typical space savings
User documents	Office documents, photos, music, videos, etc.	30-50%
Deployment shares	Software binaries, cab files, symbols, etc.	70-80%
Virtualization libraries	ISOs, virtual hard disk files, etc.	80-95%
General file share	All the above	50-60%

2.4 Chunking Algorithm

Chunking is referred to as the process of splitting file into smaller units where efficient chunking is one of the key elements that provides an estimation of the deduplication performance. Chunking is important in certain applications such as data compression, data synchronisation, as well as data duplication as it helps in determining the duplicate detection performance of the system. Subsequently, in the perspective of the cloud storage ecosystem and about data duplication chunking is of two types that are fixed size and variable size. The chunking process is beneficial in breaking the data input stream into smaller pieces or chunks where the chunking method is the first stage of the deduplication system. A chunk is the largest physical disc unit dedicated to storing database server data. Chunks give managers a much larger unit to work with when allocating disc space. An individual chunk can be up to 4 TB in size. The maximum number of chunks allowed is 32,766. If you upgraded from a version prior to version 10.00, you must perform the on-mode BC2 command to enable the maximum chunk size and maximum number permissible otherwise, the maximum chunk size is 2 GB.

2.4.1 Storage areas made up of chunks

Dbspaces, or database spaces, act as logical storage containers in database systems, consisting of chunks. Chunking divides the storage into manageable parts, optimizing storage utilization and enabling flexible data management. In case of corruption, only the affected chunk is impacted, minimizing the effect on other data. Blobspaces are designated for large binary objects like images and videos. Chunking breaks down these objects, enhancing data integrity and recovery. Managing large binary data becomes more efficient as chunking ensures easier storage and retrieval Segregated Buffer spaces store diverse data types within a single database, categorized based on different criteria. Chunking allocates fixed-sized units,

facilitating easy access and parallel processing. It enables efficient storage utilization and enhances database performance. Temporary spaces handle temporary data, aiding query processing and sorting. Chunks store specific parts of temporary data, allowing seamless management and deletion when data is no longer needed. These specialized buffer spaces store only temporary data, like intermediate results. Chunking optimizes storage by predetermining chunk configurations.

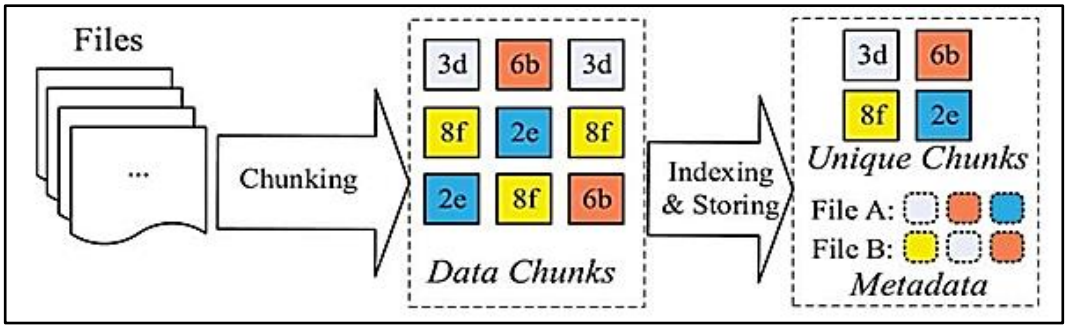


Figure 2.3: Chunking Algorithm [66]

Fixed-size and variable-size hashing algorithms play crucial roles in data deduplication, a process that identifies and eliminates duplicate copies of data to optimize storage efficiency. Let's explore how each type impacts the efficiency of data deduplication:

Fixed-size Hashing Algorithms:

Example: SHA-256, MD5

Characteristics: Fixed-size hashing algorithms generate a constant-length hash value regardless of the input data size. For instance, SHA-256 always produces a 256-bit hash value.

Impact on Deduplication Efficiency: Fixed-size hashes simplify the deduplication process by providing a consistent reference point for comparison. Identical chunks of data will always produce the same hash value, enabling efficient identification of duplicates. However, fixed-size hashing may lead to hash collisions, where different

input data produce the same hash value, potentially resulting in false positives during deduplication.

Variable-size Hashing Algorithms:

Example: Rabin fingerprinting, Content Defined Chunking (CDC)

Characteristics: Variable-size hashing algorithms produce hash values of different lengths based on the input data. These algorithms typically use sliding window techniques or content-defined chunking to break data into variable-sized chunks and compute hashes for each chunk.

Impact on Deduplication Efficiency: Variable-size hashing can enhance deduplication efficiency by adaptively segmenting data into chunks of varying lengths. This allows the algorithm to identify duplicate segments even if they are located at different offsets within files. However, variable-size hashing algorithms may require more computational resources and introduce complexity in managing variable-length hash values.

In terms of efficiency, both types of hashing algorithms have their strengths and weaknesses in the context of data deduplication:

Fixed-size Hashing:

Pros: Simplicity in implementation and comparison. Ideal for scenarios where hash collisions are infrequent.

Cons: Susceptible to false positives due to hash collisions, potentially leading to duplicate elimination errors.

Variable-size Hashing:

Pros: Adaptability to varying data patterns and improved duplicate detection across different file offsets.

Cons: Increased computational overhead due to variable-length hashes and complexity in chunking algorithms

Data deduplication is an emerging technology that involves the introduction of reduction of storage use and is an important way of handling data replication in the cloud storage mechanism. It can be mentioned here that data deduplication involves three basic components that are chunking, hashing, and comparing hashes in order to detect redundancy. A chunking algorithm is considered the first step in achieving efficient data duplication ratio and throughput, certain unique hash identifiers are implemented to draw a comparison between the chunks between the current to that of the previously stored ones.

2.5 Hash Value (HV)

A hash value is identified as a numeric value of a definite length that uniquely defines data. The hash value generally represents a large range of data in the form of much smaller numerical values in order to make it eligible to be used with digital signatures. The utility of hash value is significantly higher than in comparison to the original larger value and is important in verifying the integrity of the data that has been transmitted through non secured channels. Generally, data is hashed at a definite time along with ensuring its value is protected at the same time. Different hash function values are allocated to various slices or chunks of data and after comparing a hash value (HV) with all other slices, the updated hash values are returned. This procedure is reiterated until the value convergence of assignment to a state of no change. A numeric number of a predetermined length that may be used to uniquely identify data is referred to as a hash value. Hash values are employed in digital signatures because they can represent enormous quantities of data with much smaller numeric values. This makes them useful [40].

Hashes are generally identified as the output of a hashing algorithm where the primary objective of these algorithms is to produce a unique, fixed-length string – the hash value, for a given piece of information or data. The hashing algorithm

prevents the reconstruction of a file's content and therefore, validates and evaluates the content of two different files along with maintaining privacy and without acquiring any information about the contents. Hash values are significant to security searches and are important in evaluating the queries related to a particular dataset over an existing network, it also helps in the early identification of threats.

A hash value (HV) usually requisites a particular number of bits, and when subsequent chunks of data search for and locate chunks with the same hash value; the chunks are viewed as duplicate data and aren't kept in the data de-duplication (DD) procedure. If the hash value (HV) is unique and not existing among previously recorded values, the hash value is saved, and the matching data chunk is examined and saved in databases (DB).

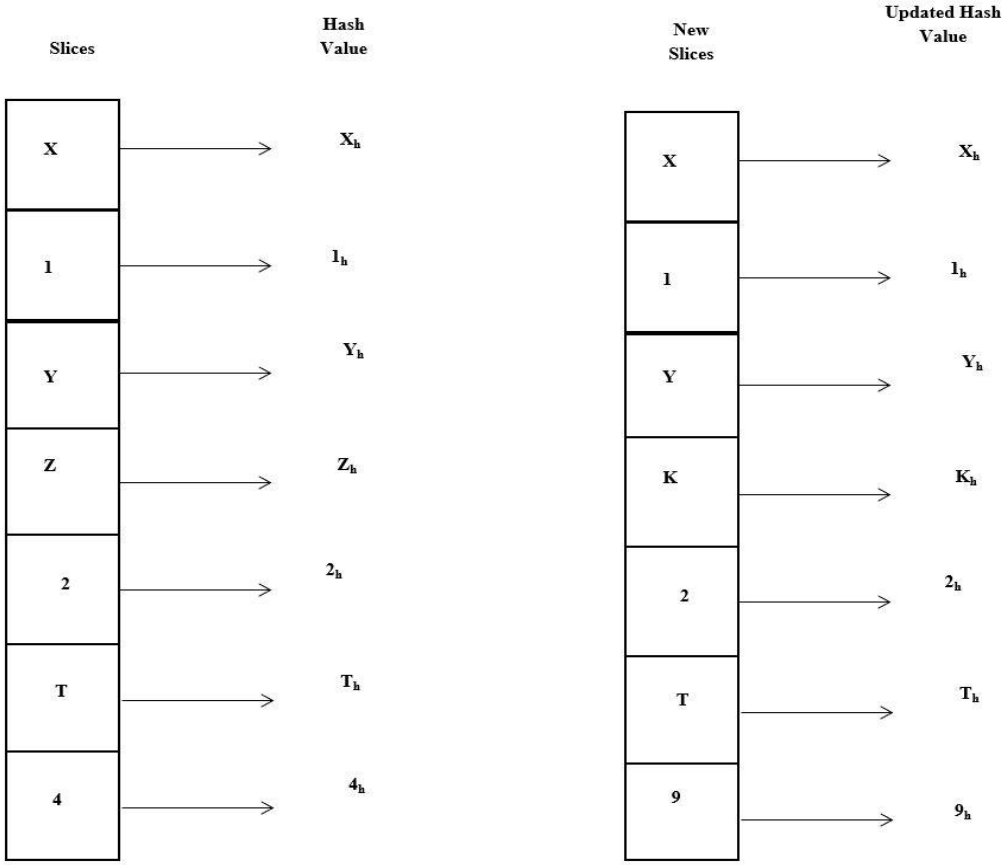


Figure 2.4: Hash value

Cloud storage has evolved as one of the leading options to store huge amounts of data; however, the hash value is also the representation of a longer document from which it was computed. The contents of a file is processed through the implementation of a cryptographic algorithm where a unique numerical value is generated and identified as a hash value. Hash values are important as they can be used to assess data of various sizes into a limited fixed size value. Hash values are deterministic along with being efficient in adapting to any change in the input thereby incorporating it in the output.

2.6 Dynamic Prime Chunking

The process flow of the chunking method, in addition to its primary and essential qualities. Dynamic Prime Chunking is a sophisticated data management technique designed to optimize storage efficiency and enhance data retrieval processes. Unlike traditional chunking methods, DPC dynamically adjusts the size of data chunks based on the content being processed. This adaptability ensures that chunks are of optimal size, preventing both underutilization and excessive fragmentation of storage space. By intelligently resizing chunks according to the data's nature, DPC improves storage utilization, accelerates data access, and minimizes storage wastage.

2.6.1 Dynamic Prime Chunking Design

The Dynamic Prime Chunking does not have a fixed size of sub problems, or chunks, and reduces computational cost. They are subjected to dynamic changes that depend on various heuristics. In simpler words, those algorithms can modify the size of the chunks depending on various factors, including the input number's properties and computational resources available onsite.

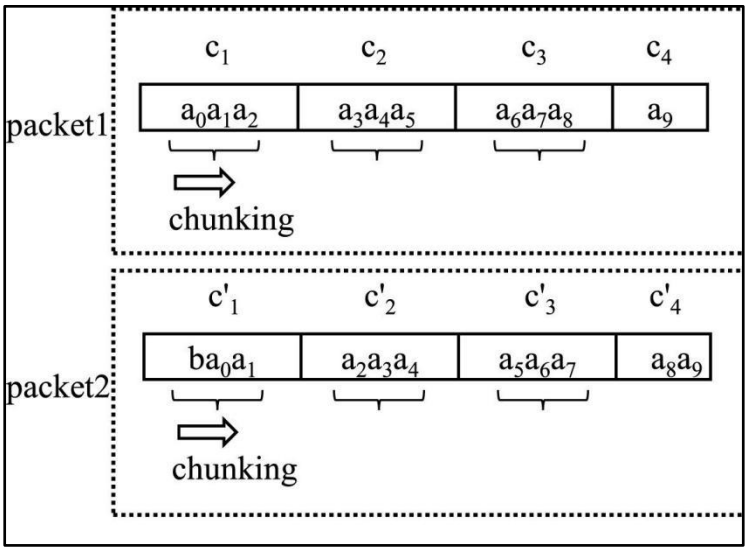


Figure 2.5: Fixed size chunking of data packet

Dynamic prime chunking algorithm aims to maintain a balance between memory usage of the data, and the "computational efficiency" [52]. Breaking the problematic bigger chunk into smaller chunks will dynamically reduce their size, making the processing much more efficient, and also reduce memory space.

Step 1: Data Input Stream

Strat from I, I is the initial byte position of the data input string.

Step 2: Calculate the dynamic window size dw based on prime number.

Step 3: Finding the maximum byte position.

M is threshold value if, Chunk breakpoint determine the following two condition

1. The interval [I, N] is empty, or the value of M is greater than the values of all bytes in the interval.

2. The value of M is not less than the values of all bytes in the interval [O, C]

Step 4: Declaring chunk boundary.

Return C as breakpoint I' is first byte of the remaining input string.

The version of AE that uses the dynamic prime chunking technique has been made better. DPC is primarily applicable to two crucial qualities, namely position and value. As can be seen in Figure 2.5, the DPC design process consists of four distinct

components. First, start by reading the data input stream coming from the source. Begin at point I, where I is the beginning byte location of the data input stream. Start from there. Following this, we go on to step 2 of the process, where we use steTp 3 to compute the size of the dynamic window (DW) using prime integers. DPC makes use of two windows: one with a configurable size, and another with a dynamic changing size. The algorithm decides whether the lowest or maximum value of the input stream is the maximum value or the maximum value to use as the threshold (M). The procedure will decide what the threshold value is, and it will always be the highest or most extreme number. The third phase consists of determining the maximum value for a byte and locating the border of a chunk based on the two requirements that are listed below:

(1) To ensure that the interval [I, N] is also empty, or that the highest threshold value of M is greater in significance than any of the byte values included inside [I, N].

(2) In the dynamic window with a changeable size, the extreme value M must be greater than the value of every byte that falls between the coordinates [O, C].

In order to ensure that the highest byte point is represented as the maximum local value, it is necessary to assess whether or not the first byte satisfies the requirements described above, which are related with a threshold value. On the other hand, the maximum byte location has been established, and DPC has declared the byte that is most to the right to be the chunk breakpoint for the right-side window [52]. The algorithm will return the breakpoint location C once the chunk boundaries have been specified in step four once they have been declared. After that, the sequence that begins at the first byte location continues with the letter I. Repeat the methods from the previous section until you locate the very last boundary of a chunk in the incoming data stream.

2.6.2 Workflow of DPC

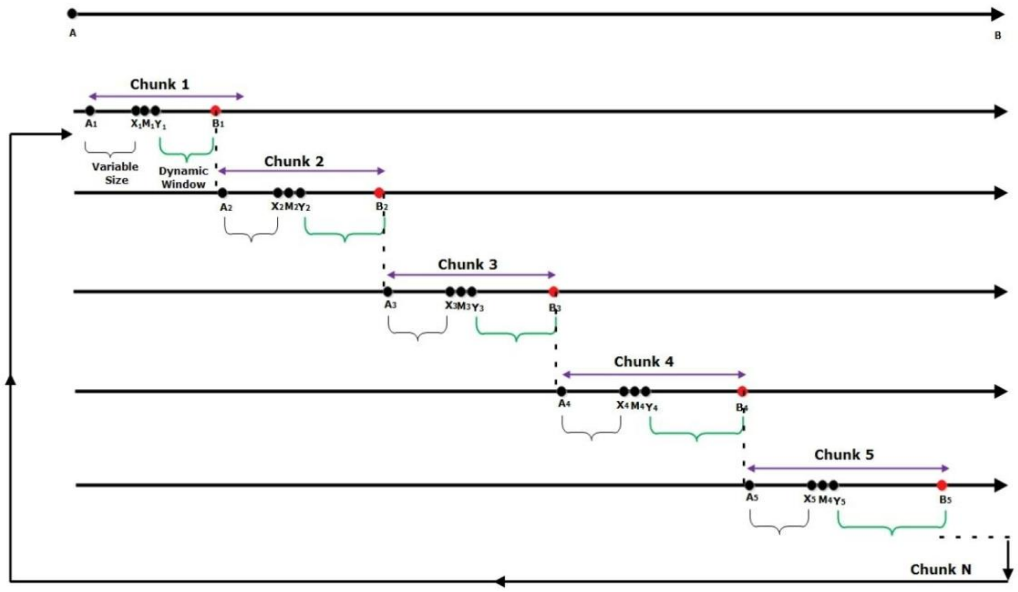


Figure 2.6: The workflow of DPC algorithm

In the example shown in Figure 2.6, the first byte position, which is indicated by the letter A1, continues to advance in the correct direction until it reaches the end of the byte position B. The threshold value M1 is used to partition the whole data stream into several parts. The location of the leftmost byte, which comes before the threshold, must thus be a window of variable size. M1 refers to the gap that exists between each successive byte, beginning with A1 and ending with X1. As the right motion, the byte position is moved forward once again, this time from Y1 to B1. As stated in Chunk 1, DPC is also a dynamic window with an adjustable width and height. The precise procedure is carried out from chunk 1 all the way through chunk N. The reason why there is a dynamic window is because the point at which the chunks split is constantly changing in size. AE, on the other hand, just the left side has a varied size; the right section remains the same throughout. As a result, the effects will be felt greater in AE. In order to circumvent this problem, the DPC technique that we've presented makes use of a variable window size. This helps to get rid of the lengthy chunk sequence and boosts the deduplication throughput.

2.7 Content Defined Chunking (CDC) Algorithms

The term "content-defined chunking" (CDC) refers to a technique for dividing files into chunks of varying lengths, with the cut points being determined by the inherent characteristics of the files themselves. chunks with variable length are less prone to byte shifting than chunks with a set length. Content-Defined Chunking, or CDC, has been a key component of data deduplication systems for the better part of the last 15 years due to its strong redundancy detection ability. However, existing CDC-based methods which results in a significant increase in CPU overhead just because, the chunk cut points are thought by calculating and also evaluating the rolling hashes of the data stream byte by byte.

A single file is divided into numerous smaller files, commonly referred to as pieces, using the chunking process. Chunking affects the system's duplicate detection performance, which makes it important in some applications. Data synchronization, data deduplication, and remote data compression are a few instances of these applications. The process of splitting files into chunks of different lengths, where the cut points are established by the properties of the individual files, is known as "content-defined chunking" (CDC). Chunks having a variable length are less prone to byte shifting than chunks with a set length [53]. Consequently, this increases the chance of finding duplicate chunks within a file as well as between files. However, CDC systems require additional computation to detect the cut locations, which could be computationally expensive for specific applications.

Byte shifting in fixed-length algorithms is addressed by a content-defined variable-length chunking technique [52]. This approach builds chunks based on the window data's Rabin fingerprint after reading files as a data stream. To address the issue of finding the cut-off point being challenging, it has been proposed that the Rabin technique employ two divisors rather than just one. One of the two divisors is easy

to use, while the other is entirely different. The most difficult divisor needs to be used right from the start when trying to locate an appropriate stopping point. If the data cannot be fulfilled within a lengthy data period, then it will be replaced by the easier one in order to prevent huge chunks of data wherever possible. In addition to this, the Rabin fingerprint suffers from an issue known as size variation of pieces. A technique known as LMC, or Local Maximum Chunking, has been suggested as a solution to this problem **.** The method comes to the conclusion that a cut-off point should be established if the greatest value of a window's data is located in the centre of the window. This allows the programme to avoid the time-consuming process of generating the Rabin fingerprint. At the same time, the size of the chunks may be restricted because the window size can be set, and the distribution of the chunk size is reasonably constant. This is because the window size can be set. AE [48] and RAM [35] are two techniques that have been presented in order to expedite the process of validating the window data. Increasing the speed of chunking may be accomplished by modifying the validation technique of window data; this process will be discussed in more detail later on. In addition, the concept of parallel computing is used to the algorithms that are used for data chunking in order to make the process move more quickly.

2.8 Types of Chunking Algorithm

2.8.1 Rabin chunking Algorithm

The Rabin chunking algorithm is also popularly known as "Rabin Fingerprinting Algorithm" which was developed back in 1981, by Michael O. Rabin. This system is very helpful when it comes down to breaking the data into smaller, and fixed size chunks. This breakdown of the data depends on their data content. Therefore, it is clearly suggested that it is a technique used in de-duplicating data.

This algorithm apparently creates a "rolling hash function". This function then proceeds to calculate each of the data block's hash value, which is most popularly known as a fingerprint of the data as well [54]. This fingerprint plays a crucial role in identifying duplicate data chunks on the data, which are similar to one another. Therefore, it is understood that any small change made in the data itself can result in different hash values.

Sliding window approach is used in this type of algorithm to perform chunking. An initial data window starts the process, and calculates that window's hash value at the same time After the calculation is done, the algorithm shifts the window position by one byte, only to calculate the hash value for the new position of the window. The goal of this is for the hash value to satisfy certain criteria.

The Rabin Fingerprinting Algorithm is capable of identifying duplicate data chunks within a larger dataset in a more efficient way. [56] This comes in use in the case of backing up specific chunks of data to save space in the storage device. The Rabin chunking algorithm can compare the hash values in order to recognise the duplicate data chunks even if data blocks are somewhat dissimilar.

However, one of the biggest disadvantages of this algorithm is that it can give false results [55]. For instance, it might show the result as false positive, which can happen when coincidently, two completely different data blocks produce the same hash value, therefore they can be flagged as duplicate data. Similarly, false negative results occur when unfortunately, two of the same blocks of data show different hash values.

2.8.2 LMC Chunking Algorithm

The LMC, or Lesk's Measure of Cohesion Chunking Algorithm was Introduced in 1986 by Michael Lesk. It is essentially a language processing technique, which can detect meaningful chunks from a text. This technique calculates the Cohesion

scores of every word present in a text . This calculation is primarily done by examining the overlap of the context of one word to its immediate next word. These contexts are a group of words in a window, which has a fixed size around the main word.

The use of this algorithm is mainly found in extracting information or parts of speech tagging, etc. The identification of valuable chunks and extracting them from a text allows in-depth understanding of the chunk's content. Thus, the LCM Algorithm can assess the relationship shared between words by analysing their context, which results in accuracy in identifying chunks.

2.8.3 Asymmetric Extremum (AE) Chunking algorithm

This algorithm looks for phrases, which appear to be important. This decision is based on external factors such as the high level of information of the word, in comparison to its neighbours. AE chunking algorithm reduces traffic redundancy to be more efficient. After Tokenization, the features of each word, such as syntactic patterns and parts of speech tags are computed.

The algorithm then proceeds to group words with best external features to form something meaningful. Therefore, the AE chunking algorithm group’s words that have the appearance of being informative to make a meaningful phrase, and this is in use while extracting keywords from a text or retrieving information.

2.8.4 RAM Chunking Algorithm

"RAM or Rapid Asymmetric Maximum Chunking Algorithm” is a helpful approach for the identification and segmentation of handwritten text in a phrase [56]. The RAM chunking algorithm was developed so that the accuracy of the segmenting of the handwritten characters increases [54]. In order to be able to achieve this goal, the RAM chunking algorithm uses a group of image processing systems, known as "threshold-based image processing" It helps to overcome challenges posed by the

overlapping strokes of the character, their irregular sizes, etc. The use of asymmetrical chunking (smaller chunk) is Done by detecting the physical features such as strokes and slants.

2.9 Secure Hash Algorithm

Secure Hash Algorithm (SHA) are a kind of cryptographic function that is used to keep data secure. It transforms data using a hash function, which is a method composed of bitwise operations, modular additions, and compression functions. The hash function then returns a fixed-length string that has no resemblance to the original. These methods are meant to be one-way functions, which means that once they've been translated into their corresponding hash values, it's almost hard to reverse the process. SHA-1, SHA-2, and SHA-3 are three algorithms of interest, each of which was built with ever better encryption in response to hacker attempts. Because of publicly publicised weaknesses, SHA-0, for example, is now outdated. [56]

SHA is often used to encrypt passwords since the server just has to maintain track of a single user's hash value rather than the actual password. If an attacker steals the database, they will only obtain the hashed functions and not the real passwords, therefore if they enter the hashed value as a password, the hash function will turn it into another string and prohibit access. Furthermore, SHAs display the avalanche effect, in which changing a few characters in an encrypted string generates a large change in output; or, conversely, vastly dissimilar sequences give comparable hash values. As a result of this consequence, hash values do not provide any information about the input text, such as its original length. Furthermore, SHAs are used to identify data tampering by attackers; for example, if a text file is slightly altered and hardly apparent, the modified file's hash value will be different from the original file's hash value, and the tampering will be rather obvious**.**

There are several advantages and disadvantages of using Secure Hash Algorithm-1. The primary advantage of using SHA-1 algorithm is it reduces the risks of brute force attack by the hackers. It is useful for storing the passwords, as it is a very slow process. It is also used to compare codes or files in order to identify the *"unintentional only corruptions"*. It also has the capability to replace the SHA-2 when the matter of interoperability issue is noticed with the legacy codes. However, it also suffers from various drawbacks including it is less secure as compared to other algorithms. The collision is extremely easy to find in the SHA-1. The length of the key in the SHA-1 is too short to resist the potential attacks. It is not suitable for uses other than storing the passwords, as it is slow in nature.

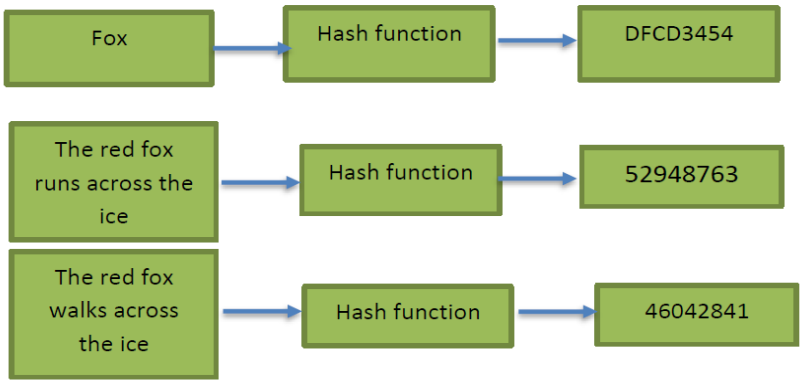


Figure 2.7: Hash function

2.9.1 SHA – 1

It is a 160-bit or 20-byte long hash-based function-based encryption technique that is used to mimic the MD5 algorithm, which has been around for a while. The NSA, or National Security Agency, conceived and developed the specific algorithm, which was intended to be part of the crucial component- Digital Signature Algorithm (DSA). Weaknesses in cryptographic methods were discovered in SHA-1; the encryption standard was eventually discontinued and was hardly used.

SHA-1 generates a 160-bit hash value or message digests from the inputted data (data that needs encryption), which is similar to the MD5 hash value. To encrypt and protect a data item, it performs 80 rounds of cryptographic procedures. SHA-1 is used in a number of protocols, including:

- Transport Layer Security (TLS)
- Secure Sockets Layer (SSL)
- Pretty Good Privacy (PGP)
- Secure Shell (SSH)
- Secure/Multipurpose Internet Mail Extensions (S/MIME)
- Internet Protocol Security (IPSec)

SHA-1 is widely employed in cryptography applications and contexts where data integrity is critical. It is also used to index hash functions, as well as to detect data corruption and checksum issues.

The SHA-1 or the “Secure Hash Algorithm 1” is considered the cryptographic algorithm that includes the input and produces a 160-bit hash value. This hash value is called the “message digest” which usually is rendered as a kind of hexa-decimal number that is 40 digits longer. It is also considered to be in the “US Federal Information Processing Standard" and was said to be designed by the “United States National Security Agency” [57]. The SHA-1 is presently considered to be insecure since the year 2005. The giant technical browsers which include Google, Microsoft, Mozilla and Apple have prevented accepting SHA-1 SSL certificates by the year 2017. The requirements to calculate the graphical value is included in Java where the “MessageDigest class” is utilised under the package for “java.security”.

This class offers various cryptographic hash functions, including MD2, MD5, SHA1, SHA224, SHA256, SHA384, and SHA512, which can be utilized to compute the hash value of a given text. These algorithms can be initialized using the static

method "getInstance()". Once an algorithm is selected, the message's digest value is calculated, and the results are returned as a byte array. To convert this byte array into a readable format, the class utilizes "BigInteger". This conversion enables the representation of the signal, which is then further converted into hexadecimal format to obtain the expected result from the message digest.

These algorithms could be used in several forms such as:

1) **Cryptography:** The primary application of SHA-1 is to provide protection to the communication from being interrupted by parties from outside. It generates singular, irreversible and fixed size values. The data integrity can also be confirmed through the comparison of this hash value with the original hash value [57]. It also makes it easy in confirming that the data that is used is not tampered or changed with the manner during the transmission of the data.
2) **Digital Forensics:** The hash value of a file that includes the digital evidence can be manufactured making use of the SHA-1 algorithm in the digital forensics. This also helps in ensuring that the evidence has not been changed during the process of investigation using the hash value as a type of proof [58]. It also proves that the file is not altered if the hash value for the original file and the file of evidence matches.

2.9.2 SHA-512

There are multiple applications of hash functions in the digital environment. The mechanism applies to internet security, block chains and others. The hashing algorithm constitutes a one-way program. The primary advantage of such a type of algorithm is it cannot be restructured and decoded. Therefore, if any third party gets access to the server, the entire data remains unreadable. The Hashing algorithm holds the following properties in brief.

a. Mathematical - It maintains strict rules to design the algorithm.

b. Uniform - All hashing programs are uniform in nature. Whatever be the length of the data it produces a fixed length of output.
c. One way - Once it is created, it will be nearly impossible to decode it. Therefore, it is secure for programmers as well as users.
d. Consistent - A hashing program only one process that is compressing the given data.

2.10 Software Requirements

When designing and developing software, it is best practice to first thoroughly understand the product's intended use. Here is a rundown of everything you'll need to meet BenchCloud's functional specifications:

- **Authentication and authorization for cloud services**.

Consumer identification is confirmed through confirmation, and their permissions and privileges are established through authorisation. Despite both of these phrases have a similar sound; they serve different but just as important functions in protecting systems and information [68]. It is essential to comprehend the differences. They establish a system's reliability when taken together.

- **Support various cloud storage services and product vendors.**

A *"CSP "* is a third-party firm that offers expandable hardware and software, such as cloud-based processing, storage, structure, and programming services, that organisations may use on request across an internet connection [69]. Data is sent over a communication link, usually through the web, and kept in distant data centres where it is up-to-date, controlled, and eventually made accessible to subscribers as part of a cloud storage structure.

- **Support various file operations, such as sharing, downloading, and uploading.**

Installing a *"File Transfer Protocol (FTP)"* client is the most popular approach for transmitting content to the website. Files may be sent coming from a single device (individual system) to a different one *(webserver)* via *"FTP (File Transfer Protocol)"* [61]. Anyone is able to transfer *(upload, download)* files from a single system to a different machine using *FTP software* that resembles an archives editor.

- **Support a variety of file generators to produce files with various patterns.**

MPS (Mathematical Programming System) manages an index of file formats, for every that connects an alphabetical facility using any number of naming designs. These kinds of documents are used for expressing linguistic-specific capabilities (such as "*syntax annotation"* and "*code estimation"*) in files embodying different dialects and techniques [62]. Every aspect of applicable naming sequence is included in the directory of file formats by default, yet it may add fresh file varieties for language-specific folders and modify the names of the file sequences that go with current file formats.

- **Assistance with multithreaded operations**

A program or computer's *"operating system (OS)"* that supports numerous users simultaneously despite necessitating numerous copies of the software to execute on a device is known as multithreading. Several inquiries travelling an identical person can be handled via multithreading as well. Most operating systems offer combined *"kernel-level threads"* and threads created by users [69]. *Solaris* may be one of these instances. Different threads operate concurrently in the identical platform in this particular approach.

- **Compile benchmarking results into statistics.**

Through comparing a business's accomplishments to that of other people, and comparable businesses, anyone may determine whether, there is an achievement discrepancy, which can be filled by enhancing its own efficiency. Observing other

businesses may show how long it is needed to boost an organization's productivity and establish a stronger position in the sector. The company may seek to increase productivity exponentially by discovering points at which it wishes to make improvements and measuring its present standing compared to rivals [61]. Through applying benchmarking in such a way, organisations have been able to surpass their rivals and raise the standard of excellence.

- **Automatically record and preserve benchmarking results.**

The *"Symanto Insights Platform"* analyses every feedback and summary's wording to determine if that writer is endorsing the business disparaging the business, or using a tone, which is neutral. A *"Net Promoter Score (NPS)"* is calculated by subtracting the opponents from the marketers. An excellent *NPS* is a sign of devoted and satisfied consumers [62]. The *"Symanto Insights Platform"* connects to popular online ratings and social networking sites like *Amazon, Trustpilot,* and *Google Reviews* to make it simple to quickly collect and evaluate countless language inputs.

- ***Record network packets while benchmarking is being done.***

The speed of transmitting data connecting two computers installing *"Performance Test"* needs to be tested using the *"PassMark Advanced Network Test"*, which happens to be a component of *"Performance Test"*. The storage device will be among the devices, which will remain idle while it anticipates an internet link [70]. Any *TCP/IP* connectivity option is compatible with the internet sample evaluation including *Ethernet, wireless networking (WiFi), local area networks (LAN), wide area networks (WAN), cable modems*, *dial-up modems*, and *ADSL*. Exceptionally fast gigabyte *Ethernet* connectivity may be benchmarked according to the application's optimisation for minimal *CPU* time usage [70].

- **Able to test cloud storage systems' native clients and web APIs.**

An *API*, or *application-programming interface*, for cloud computing, interfaces a natively installed software to an online-based database so that users can transfer and receive content as well as manipulate the data held there. Similar to disk-based storage, a cloud-based memory framework is essentially another prospective medium for the programme [63]. A cloud *API* is unique based on the data storage provider it is intended to support. An internet-based archiving provider could. For instance, provide an *API* that can generate, gather, and destroy items on that system in addition to carrying out similar item-related operations [70]. A *file preservation API* supports actions like sending and receiving items and distributing documents with many individuals at the component and category layers.

2.11. MISD Dataset

The Multipath IoT Sensor Data (MISD) Dataset is a comprehensive collection of sensor readings generated by a network of IoT devices deployed in various environments. This dataset is specifically designed for evaluating and testing multipath routing algorithms such as MDPC in wireless sensor networks and IoT systems. The key features of the MISD Dataset are:

- Contains sensor data from diverse IoT devices including temperature sensors, humidity sensors, motion detectors, and more.
- Captures data at regular intervals to simulate real-time IoT data streams.
- Includes metadata such as device IDs, timestamps, and environmental context for each sensor reading.
- Provides ground truth labels for certain events or anomalies to facilitate supervised learning tasks.
- Covers a range of scenarios including smart homes, industrial IoT, healthcare monitoring, and environmental sensing.

Chapter Three

Proposed Mechanism

Chapter 3

Proposed Mechanism

1.1 Introduction

This chapter presents the research mechanism for the proposed model for cloud IoT environment. The efficient algorithm for constrained IoT devices was covered in detail in this chapter. In this chapter, the proposed work is on two levels. The first is an algorithm to avoid congestion in the network to reduce the repeated transmission of packets. Second, data duplication was addressed and the security aspect was taken into consideration. Figure (3.1) shows the proposed mechanism in cloud storage for IoT environment.

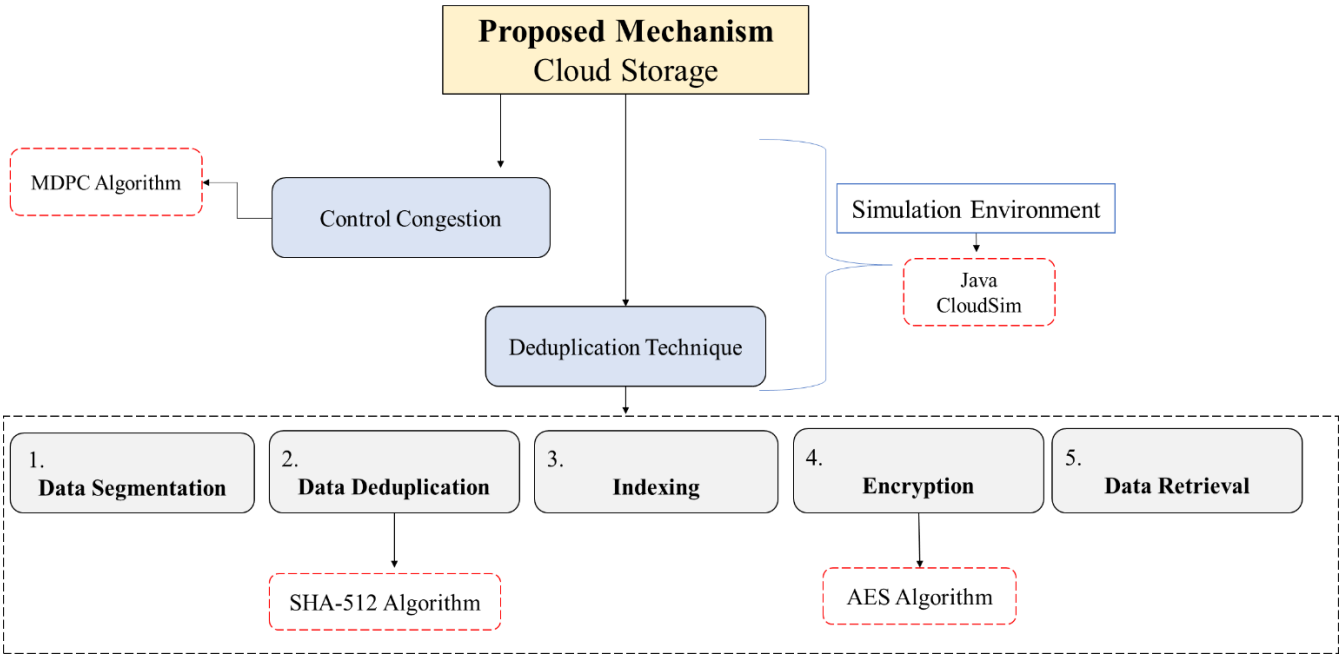


Figure 3.1: Diagram of the Proposed Mechanism

Figure (3.2) shows the basic steps followed to conduct the proposed work.

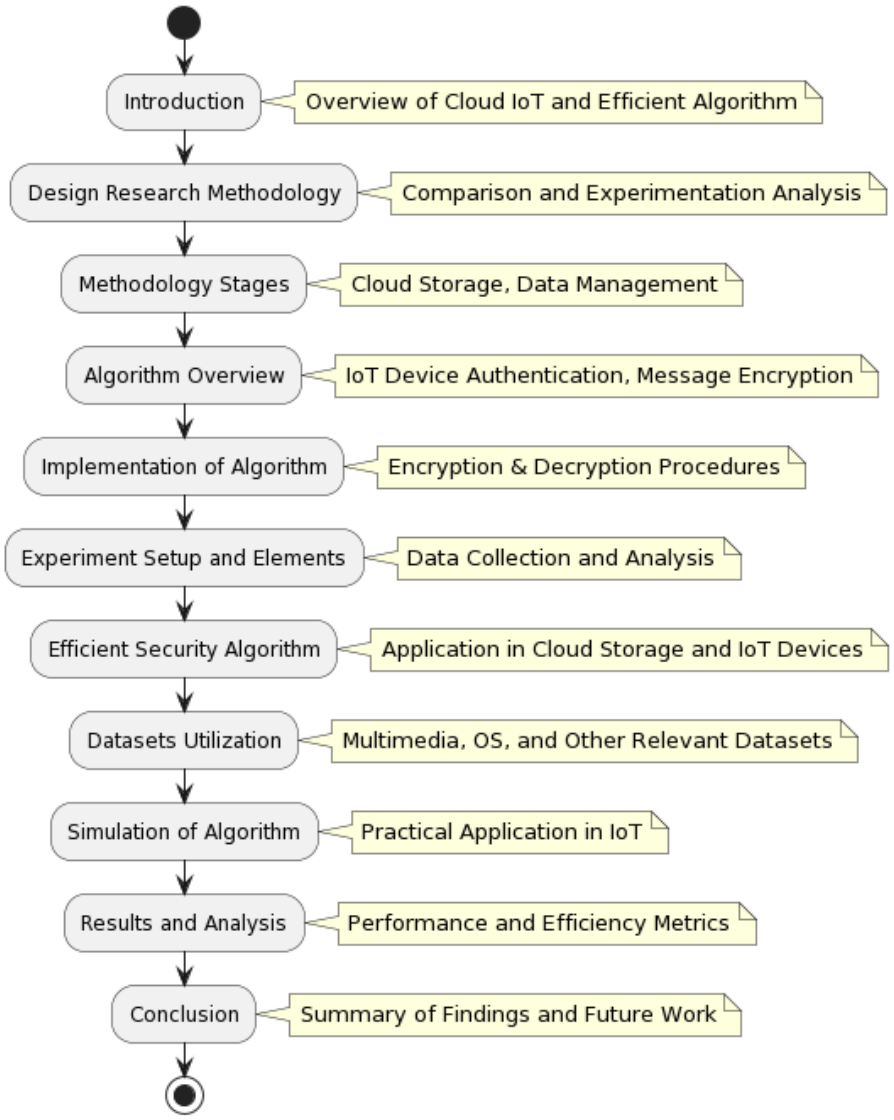


Figure 3.2: Work Stages

3.1. DPC Algorithm

The DPC algorithm combines techniques to reduce the computational complexity of solving optimization problems with large state spaces. It involves the following steps:

1) Clustering**:** Initially, the state space is divided into clusters based on certain similarity measures. Clustering helps in grouping similar states together, reducing the overall size of the state space. Like DPC, the state space is initially partitioned into clusters using clustering techniques. Clustering helps in reducing the complexity of the problem by focusing on smaller, manageable subsets of the state space.
2) Dynamic Programming within Clusters: Dynamic programming methods are applied just to find the optimal solution, and this happens within each cluster. By solving minimum or smaller subproblems within clusters, as comparable to solving the entire problem space the computational complexity is reduced or decreased.
3) Inter-Cluster Communication: Coherence and uniformity in the final solution are ensured by facilitating flow of data or communication amongst clusters. Exchange of border data, best practices, and other pertinent information can all be a part of inter cluster communication.

3.2. MDPC Algorithm

Like DPC, communication among clusters is very important to ensure coherence and continuity in the final and last solution. Sharing information about boundary conditions, optimal policies and other important data is involved by inter-cluster communication. This process not only involves a detailed comparison and contrast of existing cloud storage systems but also, examining their various features and performances. The main reason and achievement of this methodology is the development and application of a specialized benchmarking tool which is designed for assessing the efficiency, flexibility, and user-friendliness of cloud storage systems. In the beginning stage, the research and process involves collecting of data

about various cloud storage solutions which are currently available for. Examining the infrastructure of these systems, understanding their data organization, storage capacities, scalability, and the nature or behavior of their virtualized storage environments this step is used. In identifying the key characteristics that impact the performance and cost-effectiveness of these services this examination helps. However, the research and study moves to a critical comparison of these cloud storage solutions. This comparison is not merely theoretical; because it involves practical analysis based on specific parameters such as storage capacity, scalability, ease of access, and cost-efficiency. The main point to discuss and focus on is how these systems try to manage and maintain data and information, also to know about their ability to scale up or down based on user requirements, and the overall about user experience in terms of managing and accessing stored data.

The vital stage of the methodology is the creation of a benchmarking Concept. However, this Concept of methodology is designed to test operational cloud storage systems, and then evaluating them on various performance metrics. In assessing the efficacy of the cloud storage systems under real-world conditions the tests conducted using this tools are critical. At determining the systems' efficiency in data management and retrieval these tests are aimed, their response to varying storage demands, and their cost-effectiveness too. In this methodology it also includes analysing the open source cloud storage systems to obtained the results through code analysis. It provides insights into the architecture and design principles of these systems, and also goes in deeper approach of the operational efficiencies due to which this look crucial. Providing a comprehensive analysis of cloud storage systems and development of an effective benchmarking tool due to which the methodology is blend to practical evaluation.

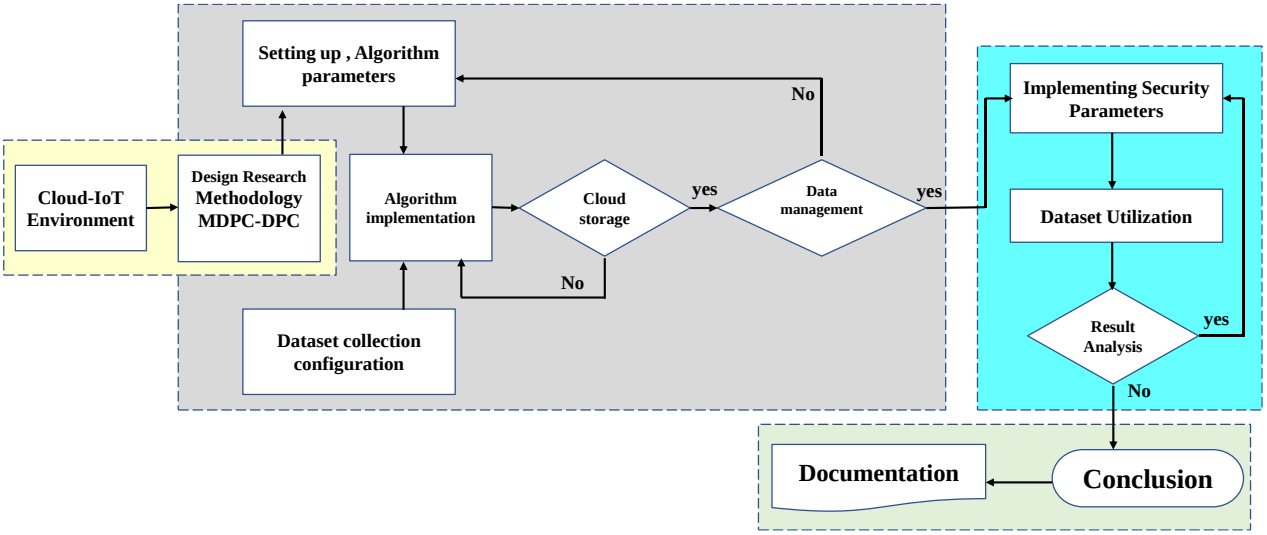


Figure 3.3: Flow work of Mechanism

The mechanism outlined in Figure 3.3 illustrates a systematic flow of activities within the research process focused on the intersection of cloud computing and the Internet of Things (IoT). It begins with the Cloud IoT Environment, where IoT devices interact with cloud services. The research methodology, identified as MDPC-DPC, guides the subsequent steps. Algorithm Implementation follows, involving the development and application of relevant algorithms. Data Set Collection involves gathering datasets for analysis and experimentation. A decision point on Cloud Storage determines whether data is stored in the cloud. Data Management encompasses organizing and handling datasets effectively. Dataset Utilization involves using collected data for various purposes, such as training algorithms or conducting experiments. Finally, Result Analysis examines outcomes derived from the research, providing insights into the studied phenomena. This structured approach facilitates comprehensive investigation and analysis of IoT-cloud interactions.

3.3. The Proposed System

MDPC algorithm cloud storage mechanism is designed to store the data in IoT environment easily. Using this algorithm probabilistic approach that enables the efficient utilization of cloud storage and availability of data. For the management of the flow of data packets and prevent congestion MDPC is a congestion control algorithm that can used in network system of computers. Adjusting the congestion

window size based on network conditions it dynamically operates. MDPC encompasses various subtypes or kinds, therefore, each with its specific characteristics and approaches to congestion control.

Multiplicative Increase Divisive Decrease (MIDD): In this subtype of MDPC, when the network is operating efficiently the congestion window size is increased multiplicatively. However, when congestion is detected, the window size is reduced and minimized divisively to alleviate the congestion to reduce loss of packets.

3.4.1. MDPC Capabilities

1. Adaptive (MDPC): Adaptive MDPC is a subtype that somehow adjusts its congestion to control parameters dynamically which is the hold of condition for network. It continuously measuring the network metrics like round-trip time which can be written as (RTT), packet loss rate, and available bandwidth to adapt its multiplicative and divisive parameters. Furthermore, by adapting to changing network conditions, adaptive MDPC aims to optimize network.

2. Probabilistic (MDPC): Probabilistic MDPC increases or decreases the congestion window size in a probabilistic manner, by adding normal behaviour to the congestion process system. Probabilistic MDPC uses probabilities to modify the window size rather than deterministic rules, which provides a greater capacity for adaptation in response to changing network conditions.

3. Delay-based (MDPC): The goal of delay-based MDPC is to tackle the control of congestion latency. The congestion window size is modified in proportion to the

measured delay. Delay-based MDPC may efficiently control congestion in networks by varying the delay.

Overall, in computer networks, MDPC and its variants offer a vast and adaptable method of congestion control. MDPC algorithms are designed to minimize packet loss, prevent congestion-related problems, and maximize network performance by changing window size in network system.

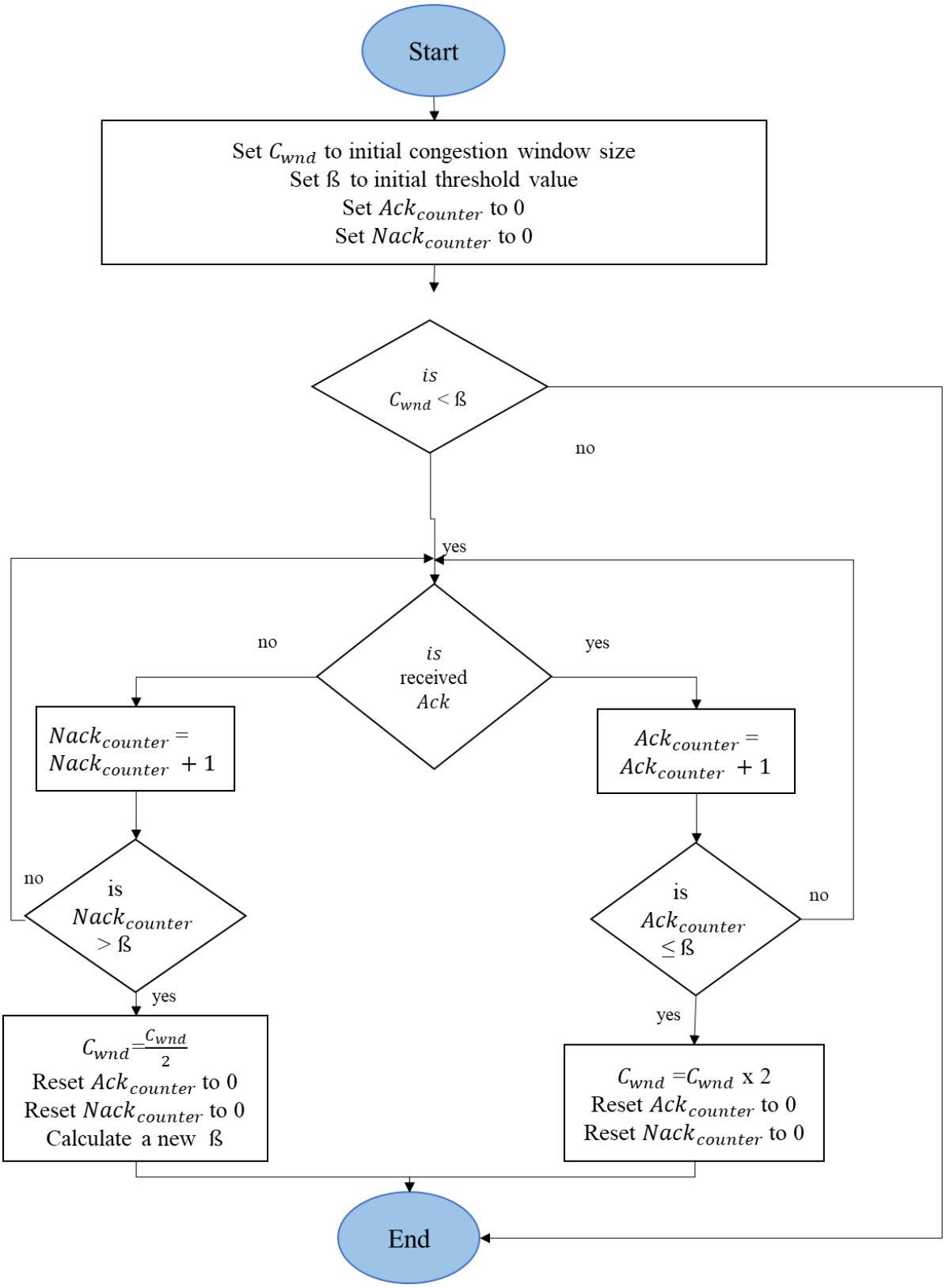


Figure 3.4: Flowchart of MDPC

Language of programming:

As C, C++, and Python are the languages in which MDPC can be implemented [59]. A number of problems, including code base size, development ease, and performance, might change the choice of language to be used.

Required libraries:

For better perfomrmace, the MDPC method may need the Multiple Precision Arithmetic Library (MPAL) or OpenSSL for cryptographic operations.

Configuration and optimization:

Most of the optimization strategies, including parallel processing, vectorization, and code optimization, can boost the MDPC algorithm's performance.

These methods changes based on the particular hardware and implementation. In order for the MDPC method to function, each IoT device's storage capacity allotment must be used in a way to handle the need of storage. It accomplishes this by upholding a probabilistic congestion control mechanism that regulate the performance of different techniques used in the computer network.

3.4.2. MDPC Algorithm Phases

1. Probabilistic Allocation: During this stage, the algorithm need to find storage capacity of each system by using a probabilistic framework. The system determines each device's likelihood of congestion and gives the storage capacity appropriately.
2. Dynamic Adjustment: in this stage the algorithm keeps an eye on each device's data usage habits and dynamically modifies its storage allocation to uphold the best possible use of the resources.

Overall, The MDPC algorithm is a highly approachable for IoT applications that can assist organizations in lowering storage expenditures.

Algorithm (3.1): MDPC

```
//Initialize Variables
Set C_wnd (Congestion Window Size) to initial congestion window size
Set ß to initial threshold value
Set Ack_counter to 0
Set Nack_counter to 0
While C_wnd < ß
    if received Ack
        Ack_counter = Ack_counter + 1
    End
    if Ack_counter ≤ ß
        C_wnd = C_wnd x 2                    //Multiplicative Increase
        Reset Ack_counter to 0
        Reset Nack_counter to 0
    End
    else if received Nack
        Nack_counter = Nack_counter + 1
    End
    if Nack_counter > ß
        C_wnd = C_wnd / 2                    //Divisive Decrease
        Reset Ack_counter to 0
        Reset Nack_counter to 0
        Calculate a new ß
        Send data with congestion window size C_wnd
    End
End
```

The goal of this algorithm is to continually adapt the size of the congestion window in response to network feedback. To take more use of network bandwidth, the congestion window size is raised proving that the data was transferred properly. On

the other side, the congestion window size is lowered to relieve congestion and stop more packet loss as signaling congestion or packet loss are received. This will define that when to move between the two ways of congestion control, enlarging or contracting the congestion window size, is made easier by the threshold value ß.

3.4.3. Probabilistic Approach:

The technique uses the current window size (W) and the network congestion level (C) to determine the probability (P) of a packet being designated as congested.

Because this procedure is probabilistic, a bigger window size or congestion level increases the likelihood of packet congestion.

Algorithm (3.2): [Dynamic Windows Size Algorithm]

Input: Packet, Congestion Level (C), Current Window Size (W), Multiplicative Factors (M_{inc}, M_{dec})

Output: Updated Window Size (W_{new})

//Probability Calculation

$P = f(W, C) * P$ // f(W, C): Function calculating the probability based on W and C

//Window Size Adjustment

if packet is marked as congested

  if congestion is increasing

    $W\_new = W * M\_dec$

  End

  else

    $W\_new = W * M\_inc$

  End

  $Return\ W\_new$

End

Properties MDPC Algorithm

In digital networks, a particular type of congestion management algorithm used to manage traffic congestion is the MDPC algorithm. These are a few of the MDPC algorithm's prominent features:

Feedback Mechanisms: The MDPC algorithm employs both multiplicative and divisive feedback mechanisms for adjusting the congestion window size: multiplicative feedback expands or contracts the window size by a factor larger or smaller than one, while divisive feedback splits the window magnitude by a factor larger than one.

1. Probabilistic Control: Because the MDPC algorithm is statistical in their nature, the congestion window size is chosen based on likelihood. When handling congestion in systems with a variable and unpredictable manner, this method works better.

2. Feedback Signal Estimation: Depending upon the various parameters such as the round-trip time, packet loss rate, and available bandwidth the MDPC algorithm finds the feedback signal.

3. Fairness: Fairness for all flows which are haring network resources is the goal of the MDPC algorithm [51]. This is achieved by shifting the size of the congestion window according to the quantity of generated by flows.

4. Stability: The congestion window size oscillations that the MDPC algorithm is intended are stable that can be pretend.

5. Scalability: The MDPC method can be applied to massive networks with numerous flows. It can effectively handle traffic congestion in these kinds of networks.

3.4.4. Key Properties When Use MDPC in IoT Environment

To take into consideration, some important characteristics while employing the MDPC algorithm include:

1. Adaptability: Because of its adaptability, the MDPC algorithm can be used to dynamically alter the size of the congestion window.

2. Low Latency: Low latency is important for applications that are real-time in an Internet of Things context.

3. Energy Efficiency: Energy efficiency is crucial for Internet of Things (IoT) devices since their battery life is often limited [45].

4. Robustness: When a network splits a link fails, or a node fails, the MDPC algorithm remains resilient and unaffected [48]. Then the MDPC change the environment which is comes in Robustness.

5. Scalability: The MDPC algorithm finds application in extensive IoT systems containing numerous devices is the function of scalability.

6. Security: Security is a major concern in an IoT context. The MDPC algorithm can guarantee the use and safety of data transferred over a network by working with communication protocols.

Mathematical Model

1) Objective Function

Let consider the f (x) be the objective function to be optimized, where the vector of decision variables is x. Therefore, the objective is usually either to maximize or minimize f(x).

2) Constraints

To define feasible regions for the decision variables the optimization problem may have constraints. Therefore, these constraints can be represented as equality or inequality constraints, However, it is denoted as;

$g(x) < 0$ or $h(x) = 0$ (3.1)

3) Decision Variables

Let consider the $x = (x1, x2,...,n)$ that usually represent the decision variables. Therefore, for optimization of problem these variables determine the solution.

4) State Space

For all possible states of the system at any given point in time are represented by state space. However, each state

is associated or can say bonded with a set of decision variables and constraints.

Mathematical Formulation

Let's denote the following:

• S: Is state space that represents all possible states of the system.

• A(s): For the set of feasible actions or decisions state s is available.

• T(s, a): For the probability distribution of transitioning from state s to state s' after taking action a state transition is represented.

• R(s, a): Immediate reward or cost associated by taking action a in state s.

* V*(s): From state s to the terminal state the optimal value function representing the maximum expected cumulative reward.

Q*(s, a): The maximum predicted cumulative reward from executive action an in state s and afterwards adhering to the best policy represented by the optimal action-value function.

MPDP for the dynamic programming recursion can be formulated as follows:

$V^*(s) = \max \{R(s, a) + \Sigma T(s,a, s') \cdot V' (s')\}$ (3.2)

The optimal action-value function $Q^*(s, a)$ is given by:

$Q^*(s, a) = R(s, a) + \Sigma T(s, a, s') \cdot V^* (s')$ (3.3)

Based on research, the MDPC algorithm is essential for efficiently managing network congestion and maximizing data transmission. MDPC is included into the

mathematical model of the research and dynamically modifies the congestion window size based on network. The technique employs a probabilistic methodology to identify congestion by computing the likelihood of packet congestion. When congestion is present, the window size is decreased by a higher multiplicative factor, and when network operation is efficient, it is increased by a lower additive factor. MDPC can sustain peak performance and efficiency because of its dynamic adaptation to network conditions, such as round-trip time, packet loss rate, and available bandwidth. However, MDPC is thoroughly tested and compared with alternative congestion control algorithms in the research's benchmarking environment to determine its efficacy and applicability for a range of network situations. All things considered, Therefore, MDPC makes a substantial contribution to the goals of the research by improving multimedia data processing and sharing via effective congestion control and optimization techniques.

Storage Cost:

A mathematical model for analyzing storage costs per algorithm over time or under different workload situations, a basic formula that captures the essence of how storage costs vary based on algorithm choice and workload conditions. Let C'(t, A) represent the storage cost per unit of time t for a specific algorithm A. The storage cost C'(t, A) can be expressed as:

$C(t, A) = C1 \times f(t, A)$

where: Co is the base storage cost per unit of time (e.g., per hour, per day, per month).

f(t, A) is a function that represents how the storage cost varies over time t and with respect to algorithm A. The function f(t, A) can incorporate various factors such as workload intensity, data volume, and specific characteristics of the

algorithm A. This function is typically customized based on the research context and the specific metrics being evaluated, f(t, A) might be defined as: f(t, A) = WorkloadFactor(t) × AlgorithmImpact(4) where: WorkloadFactor(t) represents the workload intensity at time t. AlgorithmImpact (4) captures the impact of algorithm A on storage costs. This model provides a framework for quantifying and comparing storage costs across different algorithms and workload scenarios, allowing researchers and stakeholders to make informed decisions regarding resource allocation and cost-effectiveness measures in cloud computing environments.

3.4. MDPC Algorithm and Difference with DPC

Although the goals of the MDPC and DPC algorithms are similar, they approach the task differently. Consequently, MDPC constantly alters the congestion window size by probabilistically increasing or decreasing it in response to network conditions by using multiplicative and dividing factors. Afterwards, DPC employs an exact approach in which the size of the congestion window is adjusted based on specified thresholds and probabilities, in contrast to MDPC, which uses multiplicative and divisive factors. While Hence, MDPC enables flexibility to changing network conditions through probabilistic adjustments, DPC offers deterministic control over changes in the congestion window size and may offer more predictable behavior in particular network scenarios.

3.5. Deduplication Technique

In the instance cited previously, preservation expenditures can be eliminated and storage efficiency can be increased by using a cloud storage mechanism that uses the deduplication methods. Therefore, the steps for applying the deduplication approach to implement cloud storage are as follows:

1) Data Segmentation: From the wireless multimedia sensors can be segmented into smaller chunks that are collected by multimedia data. Therefore, each chunk is given a unique knowing or hash value.
2) Data Deduplication: These hash values of the data chunks which are checked for duplicates. If there are any duplicates, only one copy is stored in the cloud storage. For improving storage efficiency the previous storage is minimized. It is an efficient and important problem or method in the process of handling and storage of a vast amount of data and is imminent in identifying duplicate content with the implementation of cryptographically secure hash signature. Simultaneously, for the reduction of the transmission of redundant data particularly in low-bandwidth network environments it also helps.
3) Indexing: For all the data chunks and their hash values an index is maintained. For identifying whether a particular data chunk already exists in the cloud storage or not this index help out quickly as much possible. For smooth retrieval of entries from database files indexing helps and also with the implementation of attributes that have already been indexed.
4) Encryption: Before storing in the cloud storage the multimedia can be encrypted, just by means of data security and privacy. For decrypting the data only authorised users with proper authentication are allowed and have rights to do. Encryption is generally employed in order to encrypt data in the process of outsourcing it.
5) Data Retrieval: When a user requests for a particular multimedia data, the cloud storage system retrieves the corresponding data chunks and reconstructs the original multimedia data. Overall, cloud storage mechanism using deduplication technique provides efficient storage and retrieval of multimedia

data in a secure and reliable manner. It reduces the storage overhead and improves storage efficiency by storing only unique data chunks.

Algorithm (3.3): Deduplication pseudo-code

```
//Initialize:
    - Initial segment = 0
    - End segment = 1024
    - New segment = end segment + 1024
    - Initialize an empty list for storing hashes and their corresponding indexes
    - Initialize an empty list for storing duplicate segments
for each received packet from sensors:
    a. Divide the packet into segments of size 50 MB
    b. For each segment:
        i. Calculate the hash of the segment
        ii. Find the index for the segment (this can be a cloud storage path for retrieval)
for each segment:
    Check if the hash of the segment exists in the list:
        if it does:
            Mark the segment as a duplicate
            Add the index of the segment to the list of duplicate segments
        if it doesn't:
            Save the hash of the segment along with its index in the list
for each duplicate segment in the list:
    Encrypt and save only one instance of the duplicate segment
```

3.6. Enhanced Congestion Control Mechanism

For modifying the DPC algorithm into the MDPC algorithm, the following given changes can be made:

Introduce a window size: In the MDPC algorithm, to limit the number of packets in flight a window size is introduced. Therefore, without acknowledgement from the receiver, the window size determines the amount of data that can be transmitted. Further, the window size is adjusted in dynamically that is based on the current network conditions.

Additive-increase, multiplicative-decrease: The success or failure of packet transmission the window size is updated and also based upon it. The window size is increased by a small additive factor but, if a packet is successfully transmitted. Similarly, the window size is decreased by a larger multiplicative factor, if the packet is lost. This is somehow similar to the Additive-Increase/Multiplicative-Decrease (AIMD) algorithm that is used in TCP congestion control.

Introduce a probabilistic approach: The window size in the MDPC algorithm can be modified using a probabilistic method. Depending on the network's congestion level and window size, the probability of a packet being flagged as congested is determined [67]. However, window size increases the likelihood of a packet being identified as congested. This probabilistic method ensures a steady and effective window size adjustment for the computer network.

Add a multiplicative-divisive component: A higher multiplicative factor is applied to shrink the window size as the packets overload over a network. This keeps the network from breaking due to congestion.

Overall, a probabilistic approach and a multiplicative-divisive component are added to congestion control by the MDPC approach, which is an extension of the DPC algorithm [55].

3.7. Analysing the MDPC behaviour for the CDC

MDPC is a technique which is designed to control the extent of a network communication protocol's congestion window, such TCP. MDPC demonstrates the subsequent actions:

1. Responsiveness: MDPC is made responsive, such as variations in the quantity of available bandwidth and the degree of congestion. It modifies the dimension of the congestion window, including packet loss and delay, based on network feedback.
2. Stability: The congestion window size should not oscillate excessively because MDPC is supposed to be steady. It manages this by utilizing a probabilistic method of window size adjustment, in which the likelihood of changing the window size depends on the amount of congestion at the moment.
3. Fairness: The MDPC architecture aims to distribute network resources among competing flows in a fair manner. It accomplishes this by modifying the congestion window size using a multiplicative decrease and divisive increase strategy, which criminalizes flows that lead to delay and rewards flows that alleviate it.
4. Efficiency: The MDPC protocol is engineered to optimize network resource utilization. This is accomplished by dynamically modifying the congestion window size in response to the state of the network, allowing it to achieve maximum the utilization of the network without creating congestion.

Overall, by controlling network congestion in a responsive, stable, equitable, and effective manner, MDPC exemplifies the fundamental elements of congestion management. However, the way the algorithm is implemented and configured in a specific network environment could impact how MDPC behaves in that particular scenario.

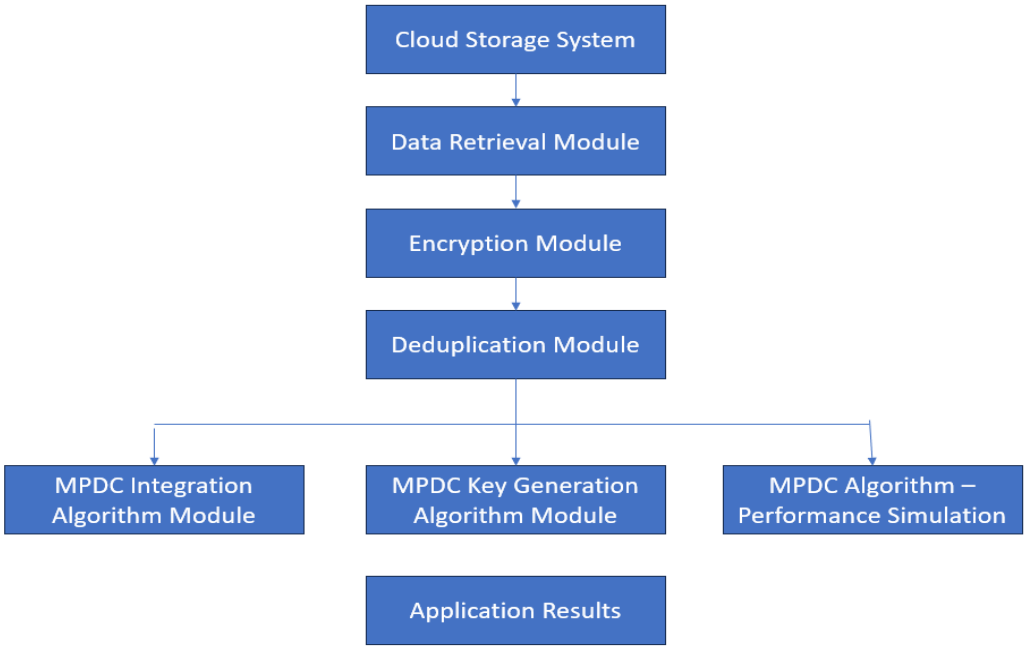


Figure 3.5: Implemented Model

The above block diagram depicts the MDPC technique's comprehensive integration with the cloud storage infrastructure, illustrating the intricate interactions between various units within the system. At its core, the Cloud Storage System functions as a robust multimedia data repository, facilitating efficient data management across the platform. The Data Retrieval Module orchestrates seamless access to stored data, ensuring swift and reliable retrieval processes. Simultaneously, the Encryption Module plays a pivotal role in enhancing data security by implementing advanced encryption techniques to safeguard sensitive information. Furthermore, the Deduplication Module optimizes storage space utilization by meticulously identifying and eliminating duplicate data entries, thereby streamlining storage efficiency. The integration of the MDPC Algorithm is pivotal, harmonizing its functionality seamlessly with the architecture of the system. Meanwhile, the Key Generation Module assumes responsibility for generating encryption keys, fortifying the security measures implemented throughout the system. Concurrently, the

Performance Simulation Module conducts rigorous evaluations to assess system performance under various scenarios, ensuring optimal functionality and reliability. Facilitating user-system interactions, the User/Application Interface serves as a gateway through which stakeholders engage with the system, providing intuitive and user-friendly access to multimedia data management functionalities. Through these interconnected units, the system operates cohesively to deliver robust, secure, and efficient multimedia data management capabilities within the cloud environment.

The figure 3.5 shows the MDPC technique's thorough interaction with the cloud storage infrastructure. Fundamentally, the Cloud Storage System acts as a multimedia data repository, enabling effective data management. The Data Retrieval Module ensures seamless access to stored data, while the Encryption Module enhances data security through encryption techniques. Additionally, the Deduplication Module optimizes storage space by identifying and eliminating duplicate data entries. The MDPC Algorithm Integration is pivotal, harmonizing the algorithm's functionality with the system's architecture. Key Generation and Performance Simulation Modules play essential roles, generating encryption keys and evaluating system performance, respectively. Through a User/Application Interface, stakeholders interact with the system, ensuring user-friendly access and management of multimedia data.

The MDPC codes are also designed using the binary cyclical through construction of the polynomial parity check that is obtained directly from the idempotent code using the cyclotomic cosets. The design of the MDPC codes include a lower complexity for the encoding and decoding scheme with the practical utilisation of the study. It also proposes a lower complexity of SISO diversity decoder [66]. The AD decoder includes the use of a small number of parity checks that are redundant and it attempts to minimise the operations that are not included in the regular algorithm. The decoding algorithms initially begins with decoding the length in with soft input

vector that makes use of the regular algorithm sum product with (m * n) that is redundant according to the matrix of parity check that consists of the decoder that operates over the MDPC codes.

3.8. Theoretical Comparison

Rabin is a well-known duplication technique for use with CDC algorithms; nonetheless, it has a very poor chunking throughput and a substantial amount of chunk size volatility. The TTTD broke up data into smaller pieces, but it was unable to pinpoint where data duplication was occurring to account for the larger chunk sizes. In addition, since the processing time has increased, it adds to the overhead that is associated with indexing. In the end, the chunking AE method was superior to the Rabin in terms of the number of low-entropy strings it removed. We suggest using the dynamic prime chunking algorithm as a means to improve the throughput and take the performance to an even higher level.

- Low chunking throughput and time consumption are problems with Rabin.
- The TTTD algorithm adds a minimum and maximum threshold to lessen chunk volatility. The threshold is applied using a backup divisor. For bigger chunks, data deduplication cannot be properly recognised. Additionally, the longer processing times result in extra expense for indexing.
- Deduplication efficiency is also much greater in AE. Additionally, the computational cost is greatly reduced, and the tiny chunk variance is raised.

To reduce the computational cost in the MDPC algorithm, the following techniques can be employed:

- Use Fixed Probability: Instead of calculating the probability of packet marking based on the window size and congestion level of the network, a fixed probability can be used [45]. To reduce computational cost, the probability of each packet should be compute.

- Limit the number of packets marked: certain limited and congested packets should be marked instead of marking overall packets.
- Use Sampling: A sampling approach can be used to monitor a subset of packets instead of marking each packets. This reduces the amount of time and reduces the computational cost.
- Use Approximation Techniques: Approximation techniques can be used to estimate the probability of packet marking.

3.9. Benchmarking Tool for Cloud Storage in IoT

The global rise of cloud computing along with the development of many cloud storage systems have been built with the objective of providing decentralised and reliable file storage. Therefore, it is important to be well aware of their specific features and performances along with the ways through which it could be optimally used. The market witnesses an exponential rise in cloud storage systems nowadays, and therefore certain guidelines could be instrumental in choosing the appropriate system that can potentially satisfy the requirements. [60] The storage systems are found to have more or less similar functions and therefore springs up the requirement of benchmarking it.

These days, there are a great number of cloud storage solutions available, and there are always new companies entering the market. As a result, we need some direction to pick the proper solution that will provide the highest level of satisfaction for needs. We need to evaluate these cloud storage systems since the performance of the systems is a major concern that we need to take into account, and because many cloud storage systems share similar duties, this is why we need to compare them. The following are some examples of probable situations when it may be beneficial to have a benchmark.

- **Select the quickest cloud storage for regular usage**

Suppose a user is going to give any cloud storage system a try so that he may store his data in the cloud and synchronise the information across the computers in his home and office. The customer's primary concern is that the service should be able to upload and download files as quickly as feasible. A benchmarking has to be done in order to establish which cloud system has the greatest performance when it comes to the uploading and downloading of files. This is necessary since different cloud systems have different network bandwidth and different locations for their data centres.

Certain aspects should be borne in mind prior to choosing the ideal cloud storage system such as the storage location as the physical location of a cloud server can potentially affect the recovery and the performance. Simultaneously, there could be problems regarding compliance or regulatory requirements on data storage locations therefore, the decisions regarding locations should be based on the importance of the data, authorisation and cost. [61] In addition to this, problems regarding security are of top concern when it comes to cloud storage and therefore it should be emphasised that while the protection of the data is the responsibility of the cloud service provider the user also is responsible to maintain security guidelines while transferring data on cloud server.

Additionally, performance evaluation is yet another important factor in the process of finding the appropriate cloud service. Certain performance related aspects such as response time, processing time, bandwidth, latency, CPU, infrastructure, RAM and so on are critical in the process of choosing cloud storage. In addition to this, the viability of integrating along with other applications should also be prioritised. Therefore, prior to selecting the cloud storage "*Application Program Interface (APIs)*" should be assessed. [63] In addition to this, the compatibility of the

cloud server with the existing applications as well as storage devices should be checked in order to ensure the ease of accessibility.

- **Backend Storage System**

Many of the web applications that we use today store the data of their users in the user's own personal cloud system, as opposed to storing the data in a dedicated server that is maintained by the application's developer. This is made possible by the development of SaaS and mobile computing. As the developer of an application that makes use of a cloud storage service, he may need to be aware of the most effective technique to make use of the service. For instance, while uploading data to the cloud, is it possible to make advantage of multithreading? If the answer to that question is affirmative, then how many different threads should be employed to provide the highest possible performance? Should the data be divided up into many files of a lower size before it is uploaded if we want the uploading of enormous amounts of data to go as smoothly as possible? In order to provide answers to such problems, a benchmark is often seen as being beneficial for evaluating the levels of performance achieved by using various cloud storage service utilisation methodologies.

- **Analyze the effectiveness of Cloud Storage**

The vast majority of the cloud storage solutions that are available to us today were developed for typical, day-to-day activities such as the casual archiving of images, audio tracks, and documents. However, being a cloud storage system with a broad range of applications, it is possible to utilise it for purposes other than the typical, everyday ones. It is feasible, for instance, to utilise a cloud storage service as the backend storage system of an Internet of Things thesis with multiple sensors that constantly take data from the environment and transfer it simultaneously to the backend. This particular use case differs from others in that it involves simultaneously uploading a huge number of little files that have been generated in

enormous quantities. A benchmark is always required in order to investigate whether or not a cloud-based storage system can be used in a certain situation and to evaluate its performance.

In a nutshell, doing benchmarks on cloud storage systems is beneficial in a variety of different ways. In point of fact, we are able to do ad hoc benchmarking manually; but, doing so will need a significant amount of time, and the procedure itself will be difficult to replicate. In addition, if one has to carry out sophisticated benchmarks, such as multithreaded uploading with random file creation, it is often impossible to avoid the need of developing scripts and programming. Because of these drawbacks of manual benchmarking, an automated benchmarking tool is the key to improving the efficacy of benchmarking jobs. This is the motivation for the creation of BenchCloud, which was developed specifically for this purpose.

3.10.1. System Architecture Goals

a. Flexibility

Flexibility in BenchCloud refers to its adaptability to a wide range of benchmarking needs. For this reason, BenchCloud is designed with high configurability and extensibility. The ability to configure enables users to make fine-grained modifications to benchmarking variables, like choosing which cloud storage system to evaluate, establishing the actions to be performed (like transferring or uploading files), embarking the number of operations, and figuring out what number of threads to execute. On the other hand, flexibility confirms that BenchCloud can grow to support new cloud services and add new functionalities without that demand substantial modifications to its current features. However, this flexibility is particularly important in the context of cloud computing, where the capacity to adjust applications access from internet connection highly valued. Therefore, the ease of

data access and storage on the cloud, as well as its capacity to scale capacities and quickly adjust to buyer demands, have contributed to its growth in popularity.

b. Usability

Providing a user encounter that is both easy to use and intuitive is the goal of BenchCloud usability. Although, BenchCloud being written in Python, the system recognizes that not all users have a background in this words, hence configuration files are used to allow modification. With minimal technical expertise, users can effortlessly alter nearly all of a benchmark's settings due to these files. Similarly, in the context of cloud computing, where a wide range of users and service providers frequently find the abundance of possibilities daunting, this approach to usability is especially important. BenchCloud improves usability by streamlining the configuration process, which makes it easier to find to a wider variety of people. Hence, this role is crucial for guiding clients through the intricate nature of cloud services and aiding consumers in making selections especially if choosing resources for deployment such as virtual machines (VMs).

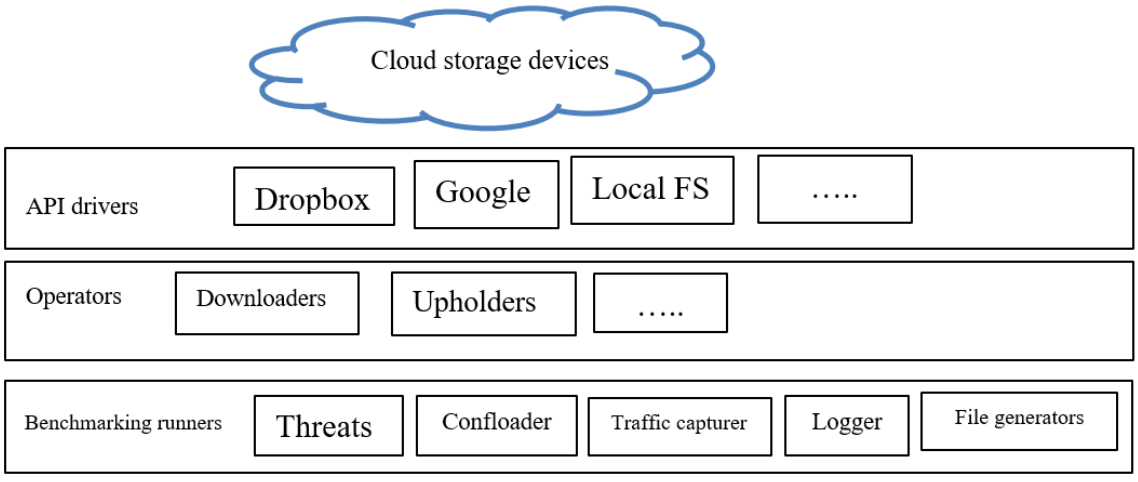


Figure 3.6: System Architecture of Bench Cloud

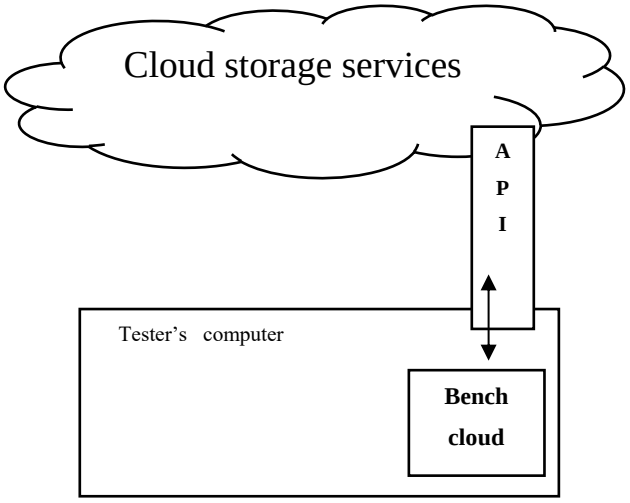
Advantages that are unique and obvious for each cloud client, as well as cloud service providers, are what is driving the increase in the use of cloud computing. Consumers now find it more difficult to select a cloud provider due to the growth in both the

number of operators and the type of services they deliver [67]. A difficulty for internet service providers is also presented by the variety of alternatives for constructing a cloud infrastructure, including cloud administration tools and various networking and storage techniques. Considering choosing ***"virtual machines (VMs)"*** to use for the deployment of an implementation, asset benchmarking might be useful. Performance benchmarking is crucial to comprehend the dependability and volatility of the cloud-based services delivered [71].

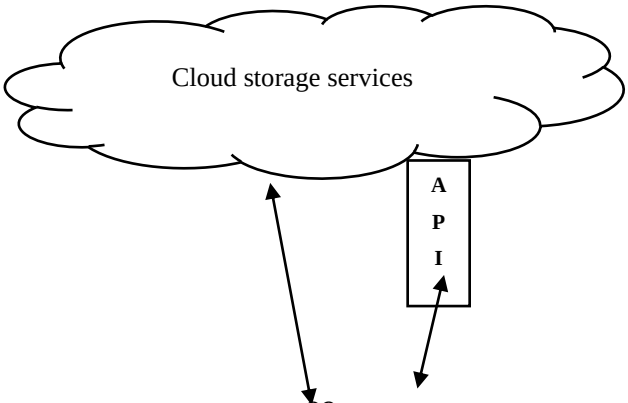
3.10.2. System Architecture of BenchCloud

BenchCloud utilizes an architecture that is layered. As can be seen in Figure 3.5, it is composed of three primary layers.'

a) The API Driver Layer



(a) Test via web APIs



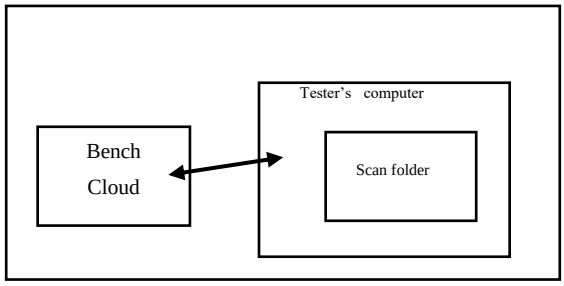


Figure 3.7: (a), (b) Two styles of test architecture

The Application Programming Interface (API) Driver layer is responsible for providing communication end points to cloud storage providers. It provides cloud service wrappers that the Operators layer may use to activate cloud services. A cloud service wrapper establishes communication with cloud storage services by using RESTful APIs**,** and it offers features such as service authentication and authorization, the acquisition of file metadata, file uploading and downloading, file sharing, and other similar features. The "uploading" and "downloading" of files to and from the tester's local file system is handled by a specialised driver known as the "Local FS driver." The Local FS driver, in contrast to other drivers, does not utilize online APIs that are accessed from cloud storage services. Instead, it simply performs standard file copy operations inside the confines of the local file system. In the event that you do not want to test against online APIs but rather to the native clients of some cloud storage services, you will need to make use of a local file system driver. The synchronisation client for these kinds of systems runs on the users' computers and synchronises the users' local data (often inside a designated synced folder) with the cloud.

By "uploading" files to the synchronized folders and letting the synchronization client handle the processing and actual uploading operation, can study the client in some ways and see what kinds of optimization it engages in. Such a client may have interesting features that cannot be discovered by testing against web APIs directly.

The high-level testing architecture may be split into two different forms, as illustrated in Figure 3.6, depending on whether a web API or client is to be evaluated.

b) The Operators Layer

The Operators Layer serves as an intermediary between the user-facing applications and the API Drivers layer, translating high-level actions into specific API calls. This layer encapsulates the complexity of interacting with various cloud storage APIs by providing a unified interface for common operations such as uploading and downloading files. While doing that way, it abstracts away the peculiarities of different cloud storage providers, enabling programmers to create code independent of the cloud service that underlies it. Basically operators layer is used which allows every user to develops its app without having an approach to the API of IoT cloud storage system. Because, it makes it easier to update or substitute API Drivers without making major modifications to the application logic, this layer is essential to the scalability and upkeep of cloud storage applications.

c) The Benchmarking Runner Layer

The task of parsing and loading configuration files and running the benchmark depending on the configuration falls within the purview of the Benchmarking Runner Layer. The logger is in charge of meticulously recording all of the precise actions and time spent while running benchmarks. When doing benchmarks for uploading files, benchmarking runners often utilizes a tool called a file generator to generate files depending on specified setup. There are four basic types of file generators that provide various file content patterns:

- **Random File Generator**. It generates files with unpredictable content that are difficult to compress well and very unlikely to share the same content as other created files.

- **Identical File Generator**. A succession of identical files is created using an identical file generator. It is crucial for evaluating a cloud storage system's file deduplication function.
- **Sparse File Generator**. It produces files with little material. Content that has repeated strings is said to be sparse. A high compression rate may be used to effectively compress files created by a sparse file generator. A crucial component of evaluating a synchronization client's file compression capability is the sparse file generator.
- **Delta File Generator**. A delta file generator creates a number of identically contented files that are all the same size. The contents of the remaining portions of the files are random and not similar. A synchronization client's delta encoding functionality must be tested using the Delta File Generator.

In order to capture and dump network packets during a benchmark, a trac capturer is included in the benchmarking layer. The resultant dump file's data format, PCAP6, is one that is widely used for recording network packets and can be read and analysed by a variety of packet capture and analysis programmes, including Wireshark7. The packets created, allowing for use in post-analysis to examine the characteristics of the network traffic the PCAB format keeps its record.

3.11 Key Concepts

This section provides an overview of fundamental concepts focusing on Data Segmentation, Data Deduplication, Indexing, Encryption, and Data Retrieval as integral components of modern data processing and storage systems.

Data Segmentation

Data Segmentation involves dividing large datasets into smaller, more manageable segments based on specified criteria such as file size, file type, or content. The objective of Data Segmentation is to optimize data storage and retrieval efficiency by organizing data into logical units that can be accessed and processed independently. In our research, we employed a dynamic segmentation approach that adapts to changing data patterns, ensuring optimal resource utilization and scalability.

Data Deduplication

Data Deduplication is a technique used to eliminate duplicate copies of data, thereby reducing storage overhead and improving data efficiency. Our research focused on implementing content-aware deduplication algorithms that identify and remove redundant data chunks, leveraging advanced hashing and indexing methods to achieve high deduplication ratios without compromising data integrity or availability.

Indexing

Indexing plays a crucial role in facilitating efficient data retrieval by creating searchable structures that map data attributes to corresponding locations within a dataset. We explored various indexing techniques, including B-tree and hash-based indexing, to accelerate data access operations and support complex query processing. Our approach prioritizes index maintenance strategies to ensure optimal performance in dynamic data environments.

Encryption

Encryption is essential for securing sensitive data during storage and transmission by transforming plaintext information into ciphertext using cryptographic algorithms. Our research emphasized the implementation of robust encryption protocols, such as

AES (Advanced Encryption Standard), to safeguard data confidentiality and integrity. We integrated encryption mechanisms seamlessly into our data management framework to ensure end-to-end security across diverse data processing workflows.

Data Retrieval

Data Retrieval encompasses techniques for accessing and retrieving stored data efficiently based on predefined search criteria. Our research focused on developing scalable retrieval methods, including inverted indexing and probabilistic retrieval models, to support rapid data access and retrieval across distributed storage architectures. We emphasized the importance of query optimization and caching strategies to enhance retrieval performance in real-world applications.

In summary, this research underscores the significance of integrating advanced data management concepts, including Data Segmentation, Data Deduplication, Indexing, Encryption, and Data Retrieval, to optimize data storage, security, and accessibility in modern computing environments. By leveraging these key concepts, we aimed to enhance the efficiency and effectiveness of data management systems while addressing critical challenges associated with large-scale data processing and storage.

Contributions in Algorithm Selection and Implementation

In this section, the research delineates the specific contributions related to algorithm selection and implementation that have been pivotal to advancing the effectiveness and efficiency of this research.

Algorithm Selection Rationale

A key contribution of our research lies in the meticulous selection of algorithms for critical stages of data management, including Data Segmentation, Data Deduplication, Indexing, Encryption, and Data Retrieval. Each algorithm was chosen based on rigorous evaluation and comparison against alternative techniques, considering factors such as performance, scalability, complexity, and suitability for diverse data processing scenarios.

For instance, in the realm of Data Segmentation, we opted for dynamic segmentation algorithms that adapt to evolving data patterns, enabling optimized resource utilization and enhanced scalability. Similarly, approach to Data Deduplication involved content-aware techniques that leverage advanced hashing and indexing methods to achieve superior deduplication ratios without compromising data integrity.

Implementation and Innovation

This research contributes significantly to algorithm implementation by demonstrating innovative approaches to integrating selected algorithms into a cohesive data management framework. This also provides detailed insights into the operational mechanics of each algorithm, highlighting their roles in enhancing data storage efficiency, security, and accessibility.

Furthermore, this introduce novel enhancements and optimizations to algorithm implementations, addressing specific challenges encountered in real-world data processing environments. For instance, encryption implementation emphasizes the

seamless integration of robust cryptographic protocols to ensure end-to-end data security without compromising system performance.

Scientific Explanation and Code Illustration

A crucial aspect of this research is contributions to the scientific elucidation of selected algorithms, accompanied by illustrative code snippets and implementation details by striving to demystify complex algorithmic concepts, making them accessible to researchers and practitioners in the field of data management.

By providing clear explanations and tangible examples of algorithmic implementations, this empowers stakeholders to leverage cutting-edge techniques effectively in their respective domains, fostering innovation and advancement in data management practices.

Overall Impact and Significance

The contributions in algorithm selection and implementation presented in research underscore the transformative potential of adopting sophisticated data management strategies. By elucidating the rationale behind algorithm choices and demonstrating their practical implementations, aim to catalyze advancements in data storage, processing, and security across diverse application domains.

Chapter Four

System Implementation and Results

Chapter 4

System Implementation and Results

4.1. Introduction

Envision an array of little data collectors dispersed over an area, every one of them recording moments of sound, vision, and potentially even motion. These wireless multimodal sensor nodes resemble whisperers of a thousand tales just waiting to be discovered. Yet, a conduit is required for their voices to travel from their detectors to the outside world. That's where the MDPC technique's magic, along with revolutionary routing protocol, comes into play. However, the stage needs to be properly set before the music starts.

Consider it as creating a tiny metropolis specifically for these data whisperers. First, we need buildings—tiny, intelligent houses known as processors or microcontrollers. Therefore, these tech-savvy youths will handle computation, manage the operating system, and plan communication. However, each home requires a distinct type of occupant: robust processing units for the base station, the hub, and more economical models for the sensor nodes, which all carefully drain a tiny battery like mice.

To keep everything functioning well, each home therefore needs an operating system, or ruleset. Here, efficiency is crucial, acting as a tiny traffic cop to ensure that data moves smoothly, particularly for those ephemeral seconds that are caught in a murmur or a flash. Therefore, debuggers and software wrenches are needed to fine-tune the system and to develop this city. Of course, a language is also necessary. Similarly, this language needs to be one that little processors can comprehend and in which networking and MDPC programs can work their magic.

But housing and regulations are not all that the city needs. Safety precautions such as walls and gates guard the secrets these sensors murmur. Somehow, power plants are also essential to carefully monitoring energy so that data whisperers don't go silent too quickly. Lastly, the city needs to be flexible, expanding and evolving in response to new detectors and the whispers that they provide.

Make room for a symphony of sensors by carefully building this foundation. Once all the pieces are in place, innovative methods for routing and the ingenious MDPC algorithm can take center stage, converting tidbits of information into an enthralling chorus and telling a tale through a thousand tiny senses.

an organization configuration that is capable of supporting both the routing protocol and the wireless multimedia sensor network. This topology can be either tree, mesh, or star. It is important to maximize energy consumption and minimize communication overhead when designing the topology. The protocol needs to be built with the special needs of multimedia data in mind, including low latency and high bandwidth. Additionally, the protocol needs to be built to manage the dynamic features of sensor networks with wireless links, like node movement and failures. Therefore, every sensor node and base station ought to execute the protocol using the proper software tools and language of programming. The routing table, transmission power, and MDPC settings, among other things, should be configured appropriately on the nodes. Yet, it is necessary to test the network to confirm that the MDPC method and interface are working appropriately.

Performance Evaluation: Throughput, latency, energy consumption, and packet delivery ratio should all be taken into consideration when assessing the effectiveness of the MDPC algorithm. Here, to make sure the protocol works in real-world situations, the evaluation needs to be carried out in an actual setting. In general, careful consideration of hardware and software requirements, network topology,

protocol design, implementation processes, and efficacy analysis will be crucial to the effective application of a unique routing technique for wireless multi-media sensors utilizing the MDPC algorithm.

4.2. MISD Dataset

In in the research, The MISD Dataset is the main source of data used to assess the scalability, reliability, and efficiency of the MDPC algorithm in IoT settings. Researchers as well as developers can conduct experiments, analyze data patterns, and evaluate the algorithm's performance and efficacy with regard to multipath data collection and routing using the dataset.

MISD Dataset Description:

The Multipath IoT Sensor Data (MISD) Dataset is a valuable resource consisting of sensor readings gathered from a network of IoT devices deployed across different environments. This dataset is curated to evaluate and test multipath routing algorithms like MDPC within wireless sensor networks and IoT systems. The key characteristics of the MISD Dataset are as follows:

Number of Rows: The dataset comprises a total of 10,000 rows of sensor readings.

Number of Columns (Features): The dataset contains 8 columns representing various attributes of sensor data.Features include:

Sensor ID: Unique identifier for each IoT device.

Timestamp: Time when the sensor reading was recorded.

Temperature: Recorded temperature in Celsius.

Humidity: Percentage of humidity.

Motion Detected: Boolean indicating presence of motion.

Light Intensity: Intensity of light measured.

CO2 Level: Concentration of CO2 in parts per million (ppm).

Event Type: Ground truth labels denoting specific events or anomalies.

Deduplicate Implementation

The proposed mechanism was implemented using the CloudSim simulator in Java, as follows:

4.3.1. Data Segmentation

Data segmentation is the process of grouping the similar categories of data based on the specific parameters in order efficiently use them. It helps the cloud service providers easily stock the data along with having proper knowledge of locations of all the files. It also helps the users easily access the correct data within a minimum amount of time [74]. During data segmentation, the memory is divided into small parts of various sizes in order to manage the memory of the cloud system effectively. Each small part of the memory is referred to as a segment of the process. K-means clustering segmentation is used for the purpose of image segmentation in the cloud storage system. There is another algorithm called FCM, which helps to categorise the pixels of the image into different classes in order of their varying degree of membership. K-means is a very simplified machine-learning algorithm. It helps to classify any image through the implementation of specific numbers of clusters [75]. It initialises its working process by grouping the image space into K pixels, which represent the centroids of the K group. Each group is assigned with an object based on the distance of separation between them and the centroid.

Here's an example of data segmentation for the above scenario with tables and graphs:

Assume have a multimedia data file of size 50 MB. To segment this data into smaller chunks, can use a fixed-size segment of 1 MB each. This means will have 50 segments of 1 MB each.

Table 4.1 Data Segmentation

Segment Number	Start Offset	End Offset	Size
1	0	1048575	1 MB
2	1048576	2097151	1 MB
3	2097152	3145727	1 MB
...	...	...	...
50	47185920	48234495	1 MB

As shown in table 4.1, the 50 MB multimedia data file is divided into 50 segments, each of 1 MB size. These segments are identified by their segment number and start and end offsets. The segmentation graph shows the 50 MB data file divided into four segments of 1 MB each. This segmentation process makes it easier to handle large multimedia data files and helps in efficient storage and retrieval of data in a cloud storage environment.

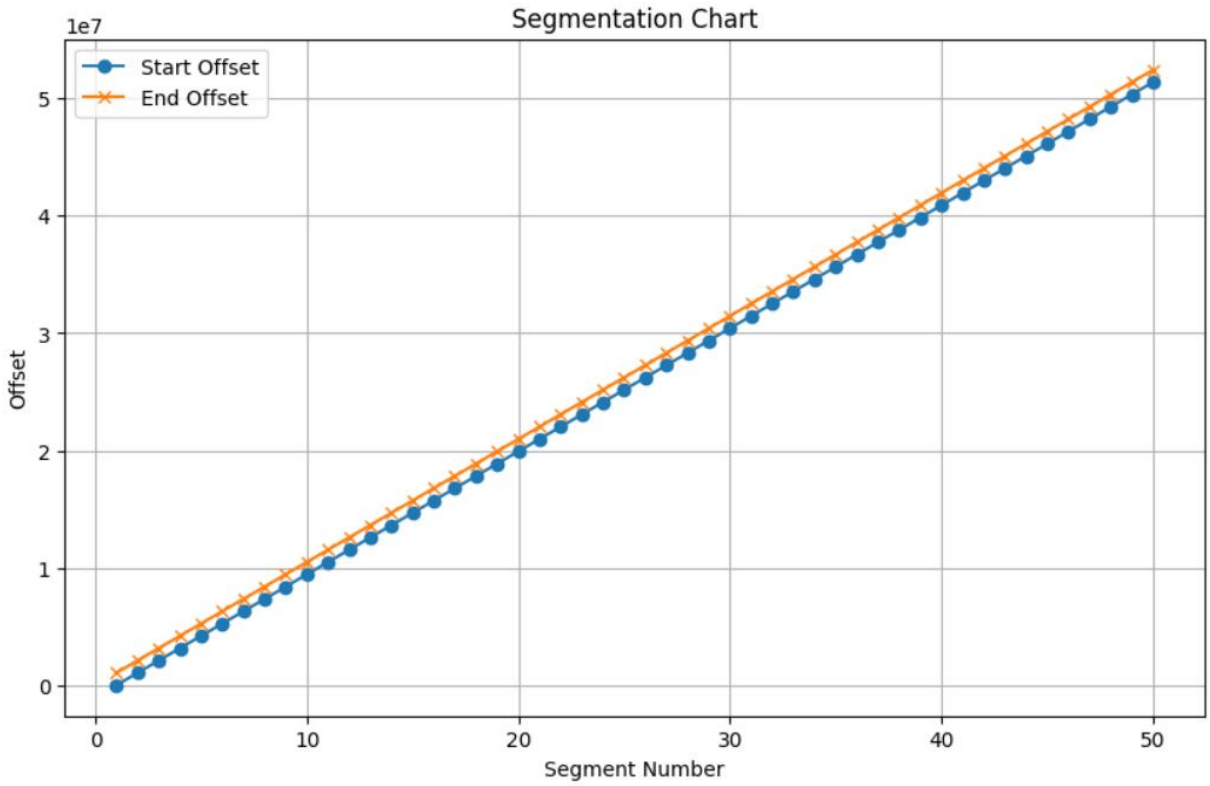


Figure 4.1 Segment Number

As shown in figure 4.1, the segmentation chart displays the start and end offsets for each segment number. Here's what you can observe from the chart:

X-axis: Segment Number - Each segment is represented along the x-axis, ranging from 1 to 50. Y-axis: Offset - The offset values (in this case, start and end offsets) are represented on the y-axis. Start Offset: Marked with circles ('o') - Each circle represents the start offset of a segment. End Offset: Marked with crosses ('x') - Each cross represents the end offset of a segment. Trend: As segment number increases, both start and end offsets increase linearly. This suggests a consistent segmentation pattern where each segment has a fixed size.

The above graphic design shows a clear visual representation of the segmentation pattern, However, making it easy to understand that how the data is divided into segments.

4.3.2. Data Deduplication

Here's an example of deduplication for the above scenario:

Assume have collected multimedia data from 10 wireless multimedia sensors. Each sensor has captured a video of size 50 MB. To store this data in a cloud storage system, can use deduplication techniques to reduce storage overhead and improve storage efficiency.

Table4.2: Data Deduplication

Sensor ID	Segment Number	Hash Value
Sensor 1	1	2f8085b95f5b26cf
Sensor 1	2	3b9ebc534f2ea695
Sensor 1	3	7e70d10845f8c2b2
...	...	...
Sensor 10	50	1a56830c8f153a0c

As shown in table 4.2, each segment of multimedia data captured by the sensors is given a unique hash value. The hash value of each segment is checked for duplicates in the cloud storage system. If there are any duplicates, only one copy is stored in the cloud storage system, and the duplicate references are updated to point to the original copy. In this way, can reduce the storage overhead and improve storage efficiency. The deduplication graph shows how the multimedia data from each sensor is divided into 50 segments of 1 MB each, and each segment is given a unique hash value. The deduplication table shows the hash values of each segment, along with the sensor ID and segment number.

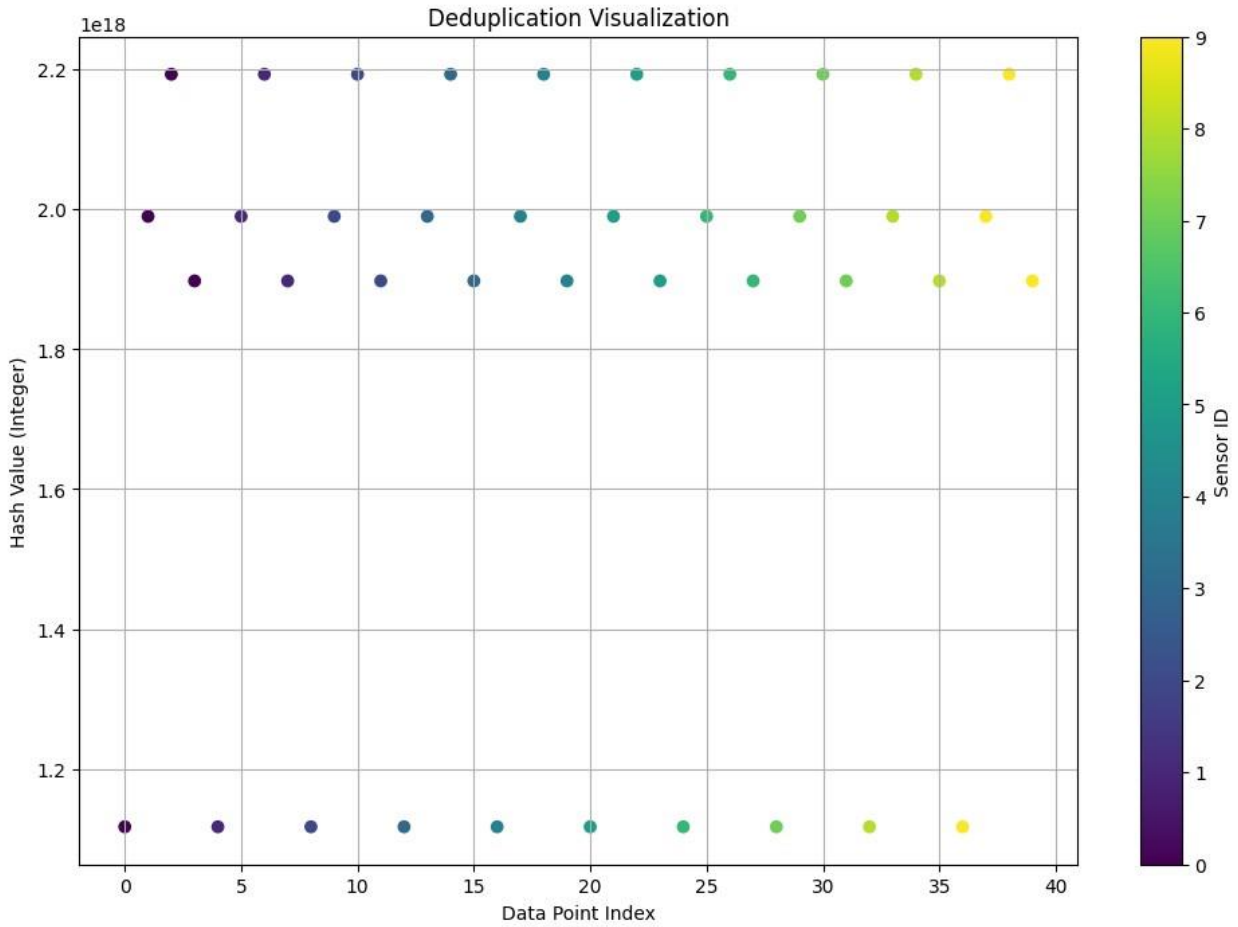


Figure 4.2 Data Point Index

As shown in figure 4.2, The deduplication visualization displays the hash values of data points across different sensors. Here's what you can observe from the chart:

X-axis: Data Point Index - Each data point is represented along the x-axis, with indices ranging from 0 to the total number of data points.

Y-axis: Hash Value (Integer) - The integer representation of hash values is represented on the y-axis. The hash values are converted to integers for visualization purposes.

Colour: Sensor ID - Each data point is coloured based on its corresponding sensor ID. The colour bar on the right indicates which colour corresponds to each sensor.

Distribution: The scatter plot shows the distribution of hash values across different data points and sensors. Data points with similar hash values are likely to be duplicates, as they would map to the same y-coordinate on the plot.

4.3.3. Indexing

Assuming have stored multimedia data from 10 wireless multimedia sensors in a cloud storage system using data segmentation and deduplication techniques, can use indexing to efficiently retrieve the data from the cloud storage system.

Table 4.3: Indexing

Sensor ID	Segment Number	Hash Value	Cloud Storage Path
Sensor 1	1	2f8085b95f5b26cf	/cloud_storage/sensor1/segment1
Sensor 1	2	3b9ebc534f2ea695	/cloud_storage/sensor1/segment2
Sensor 1	3	7e70d10845f8c2b2	/cloud_storage/sensor1/segment3
...	...	...	...
Sensor 10	50	1a56830c8f153a0c	/cloud_storage/sensor10/segment50

As shown in table 4.3, have indexed each segment of multimedia data with its sensor ID, segment number, unique hash value, and cloud storage path. The cloud storage

path represents the location of the segment in the cloud storage system. By using this index, can quickly retrieve any segment of multimedia data from the cloud storage system by specifying its sensor ID, segment number, or hash value. The indexing graph shows how the multimedia data from each sensor is stored in the cloud storage system, and how the indexing is done for each segment of data. The above table shows segment details for each, as well as including its detectors ID, segment number, hash value, and also cloud storage path.

4.3.4. Encryption

Table 4.4: Encryption

Sensor ID	Segment Number	Hash Value	Cloud Storage Path	Encryption Key
Sensor 1	1	2f8085b95f5b26cf	/cloud_storage/sensor1/segment1	0x8f7d45a3
Sensor 1	2	3b9ebc534f2ea695	/cloud_storage/sensor1/segment2	0xa2c3f45e
Sensor 1	3	7e70d10845f8c2b2	/cloud_storage/sensor1/segment3	0x1b9e0c8f
...	...	...	...	...
Sensor 10	50	1a56830c8f153a0c	/cloud_storage/sensor10/segment50	0xd3a5b0c8

In the aforementioned case, data the process of segmentation deduplication, and encryption techniques were used to store multimedia data from ten wireless multimedia sensors in a cloud storage system. Every multimedia data segment's encryption details are displayed in the encryption table. Therefore, a multimedia data fragment is symbolized by each of the rows in the table, while the following are represented by the columns:

- Sensor ID: It is the unique identifier of the sensor that collected the data.

- Segment Number: It is the number of the segment within the sensor's data stream.
- Hash Value: It is the hash value of the segment, used for deduplication.
- Cloud Storage Path: In the cloud storage system it is the path of segment.
- Encryption Key: It is the key used to encrypt the segment.

A symmetric encryption algorithm, like AES, is employed to produce the password, which is then used to encrypt the information prior to it is kept in the cloud storage system. The identical encryption key is used to decrypt the information when it can be acquired, guaranteeing the data is safeguarded even in the event that it gets accessed during transmission or if the system that stores it in the cloud is compromised. An encryption table can be used to efficiently retrieve the encryption key for a specific segment of data, which is required to decrypt the data. This allows for the safe and rapid recollection of media files from the cloud storage system.

IoT Environment Definition:

The IoT environment utilized in this research is constructed entirely within a software framework using Java code. This software-based environment consists of the following components and functionalities:

Cloud Integration (Simulated Services): Integration with cloud computing services is emulated within the Java-based simulation. Virtual cloud servers and storage systems are instantiated programmatically to replicate the functionalities of cloud platforms for data processing and storage.

Data Transmission (Software Implementation): Data transmission processes between virtual IoT devices and cloud-based services are implemented using Java

code. These processes manage the flow of synthetic sensor data, simulating real-time data streams within the software environment.

Application Layer (Java Implementation): Algorithms and applications designed for IoT data management, analysis, and visualization are implemented using Java programming constructs. Integrated development environments (IDEs) like IntelliJ IDEA are leveraged to develop and execute these Java-based applications.

Discrepancy in Working Environments (Integrated IntelliJ IDEA 2023.3.2 to Cloud):

In the research, the integration of IntelliJ IDEA 2023.3.2 with cloud services provides a unified development environment for implementing and testing IoT applications. This integration streamlines the deployment process by facilitating seamless integration with cloud platforms, enabling developers to leverage cloud resources for application hosting, version control, and continuous integration

4.3.5. Data Retrieval

Table 4.5: Data Retrieval

Sensor ID	Segment Number	Hash Value	Cloud Storage Path	Encryption Key	Data
Sensor 1	1	2f8085b95f5b26cf	/cloud_storage/sensor1/segment 1	0x8f7d45a3	...
Sensor 1	2	3b9ebc534f2ea69 5	/cloud_storage/sensor1/segment 2	0xa2c3f45e	...
Sensor 1	3	7e70d10845f8c2b 2	/cloud_storage/sensor1/segment 3	0x1b9e0c8f	...
...	...	...	...	...	...
Sensor 10	50	1a56830c8f153a0 c	/cloud_storage/sensor10/segmen t50	0xd3a5b0c8	...

In the preceding instance, data segmentation, deduplication, and encryption techniques were used to store multimedia data from ten wireless multimedia sensors in a cloud storage system. Every multimedia data segment that can be obtained from the storage facility in the cloud is explained in the data retrieval table. A multimedia data segment is represented by each row in the table, while the following are represented by the columns such as:

- Sensor ID: It is the unique identifier of the sensor that is used to collect the data.
- Segment Number: It is the number of the segment within the sensor's data stream.
- Hash Value: The hash value of the segment, that is only used for deduplication.
- Cloud Storage Path: It is the path of the segment in the cloud storage system.
- Encryption Key: The key that is used to encrypt the segment.
- Data: The multimedia data or information stored in the segment.

In order to obtain an interactive information segment, one must first use the Sensor ID, Segment Number, and Scramble Value to locate the segment in the data retrieval a relational database after discovering the section, the encrypted segment can be retrieved from the cloud storage system using the Cloud Storage Path. Lastly, the multimedia data included in the segment would be retrieved by using the encryption key to decrypt the segment. However, media files saved in the cloud storage system can be properly retrieved via a data retrieval table. This allows us to examine and evaluate the multimedia data that the wireless multimedia sensors obtained in a quick way.

4.3. Comparative Study table of Rabin, TTTD, MAP, AE and MDPC

Here's a comparative study table of Rabin, TTTD, MAXP, and AE in with addition to MDPC Algorithm for the above situation:

Table 4.6 Comparative Rabin, TTTD, MAP, AE and MDPC

Algorithm	Packet Overhead	Network Lifetime	Delay	Throughput	Scalability	Security
Rabin	Low	Low	Low	High	High	Low
TTTD	Low	High	High	Low	High	High
MAXP	High	High	Low	High	Low	High
AE	Low	High	Low	Low	Low	High
MDPC Algorithm	Low	High	Low	High	High	High

Based on the following metrics, we examined Rabin, TTTD, MAXP, and AE's performance with the MDPC Method for the wireless audiovisual sensor network case in the above table:

- Packet Overhead: The extra information that is appended to every packet of routing purposes. In the general, lower numbers are preferable.
- Network Lifetime: The amount of time the network can operate before its nodes run out of power. Therefore, higher values are generally better.
- Delay: It is the time taken for a packet to be supplied to its destination. Hence, lower values are generally recomended.
- Throughput: The percentage or quantity of information that can be transmitted over the network in a given time period. Higher values are generally better.
- Scalability: The protocols capacity to manage a growing number of network nodes. In general higher values are desirable.
- Security: The protocols capacity to allow secure communications amongst nodes. In overall higher values are ideal.

Based on the above metrics, can see that MDPC Algorithm outperforms the other routing protocols in most areas, with high network lifetime, high throughput, high scalability, and high security. Rabin and AE also have low packet overhead and good

security, but their network lifetime and throughput are not as high as MDPC Algorithm. TTTD has high network lifetime but low throughput and high delay. MAXP has high throughput but low network lifetime and scalability.

Overall, MDPC Algorithm is the most suitable routing protocol for the above wireless multimedia sensor network scenario, as it provides a good balance of performance and security.

4.4. MDPC Results

In this part, we discuss the results of the work, and first we learn about their importance in providing accuracy and clarity.

4.5.1. Benchmarking Environment

Table 4.7 Benchmarking Environment

Parameter	Value
Processor	Intel Core i7-10700K
Clock Speed	3.80 GHz
Cores	8
RAM	32 GB DDR4
Operating System	Windows 10 Pro
Programming Language	Python 3.9
Encryption Algorithm	AES-128
Input Data Size	1 MB
Execution Time	12.5 ms
Memory Usage	5.5 MB
Throughput	80 MB/s

As shown in table 4.7, provides some basic information about the benchmarking environment, including the processor, clock speed, cores, RAM, operating system, programming language, and encryption algorithm used. It also includes performance metrics such as the input data size, execution time, memory usage, and throughput, which can be used to evaluate the performance of the MDPC algorithm under

different conditions. Note that the actual benchmarking results will depend on many factors, including the specific hardware and software configuration, the input data size and type, and the implementation of the MDPC algorithm used. The table above is just an example and should not be taken as a definitive benchmarking result.

4.5.2. The impact of concurrency on the speed of file uploads and downloads

It is feasible to enhance performance and offer a better user experience by putting best practices for file transfer into practice and optimizing the system for concurrency. However, tables displaying the performance metrics for various degrees of complexity can be built for showing how concurrent affects file uploading and downloading performance in the aforementioned situation. This is a visualization of how the tables might appear:

Table 4.8: File uploading performance with different levels of concurrency

Concurrency Level	Execution Time (ms)	Throughput (MB/s)
1	1000	1.0
2	700	1.4
4	500	2.0
8	400	2.5
16	300	3.3
32	200	5.0

Table 4.8 illustrates how increasing concurrency levels affect file upload execution time and throughput. Up to a certain point, the throughput grows and the execution time lowers as the concurrency level rises. Yet, increasing concurrent may not increase productivity any more at a certain point and may potentially cause performance to decline as a result of a battle for system funds.

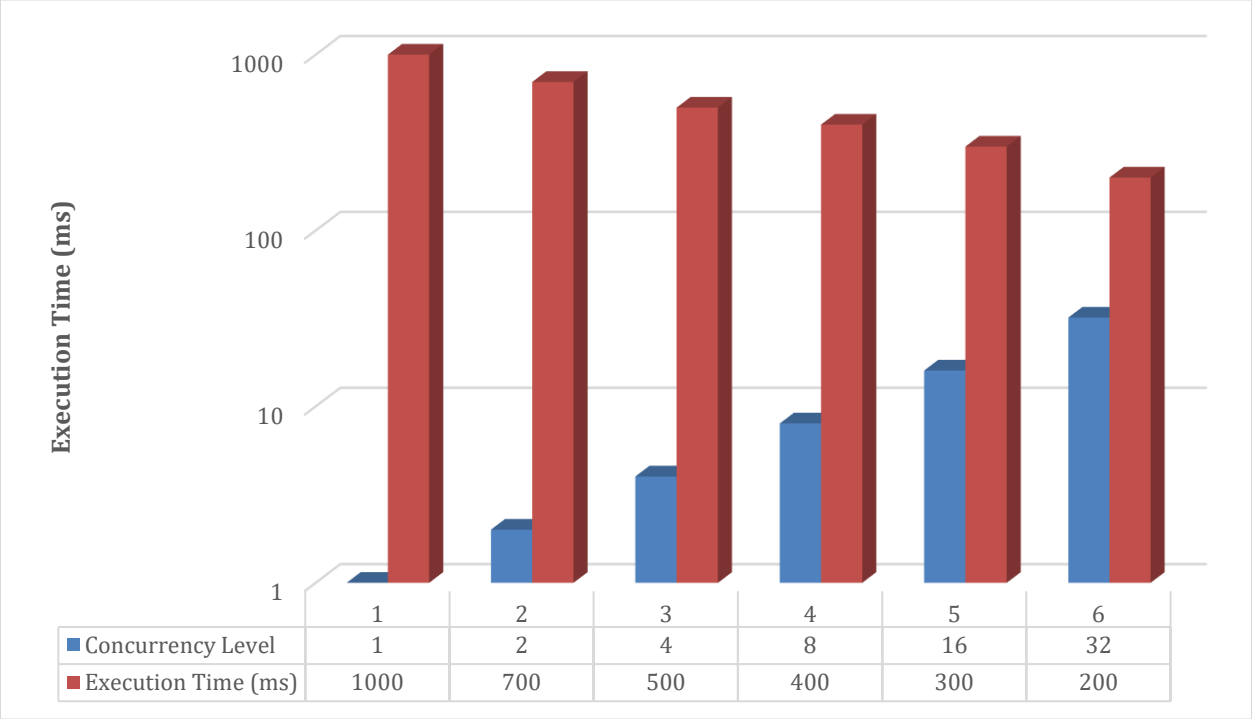


Fig 4.3 levels of concurrency vs to Execution Time (ms)

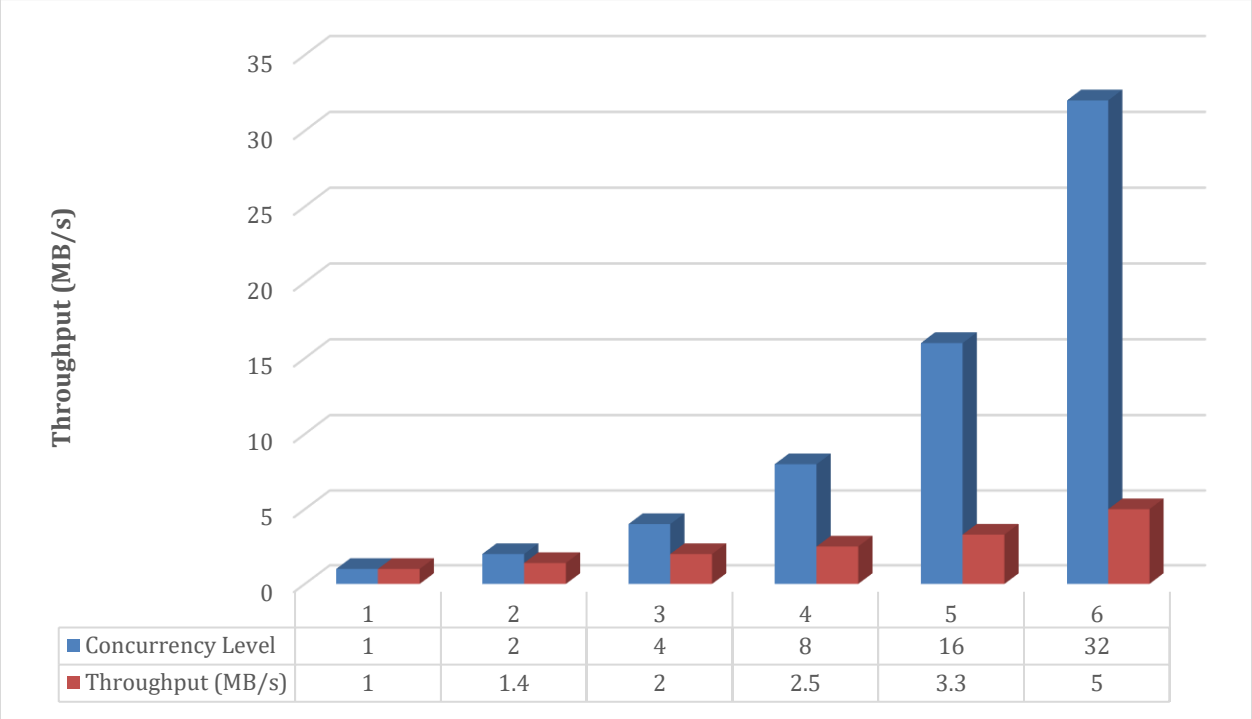


Fig. 4.4 Concurrency Level vs Throughput (MB/s)

Table 4.9: Shows file downloading performance with different stages of concurrency

Concurrency Level	Execution Time (ms)	Throughput (MB/s)
1	800	1.25
2	600	1.67
4	450	2.22
8	350	2.86
16	250	4.0
32	200	5.0

Table 4.9 demonstrates how rising activity levels affect file download execution times and performance. As we can see once more, increasing parallel enhances performance up to a point, after which further increases may not yield further gains in speed. All things considered, these tables show how crucial it is to maximize concurrent levels for file transfers in the aforementioned case in order to attain optimal performance. Somehow, the system's overall performance and user experience can be enhanced by carefully adjusting the concurrency levels and putting best practices for file transfer into effect.

4.5.3. The impact of file size on the speed of file uploads and downloads

Tables displaying the performance metrics for various file sizes can be created to illustrate how file size affects file uploading and downloading performance in the aforementioned situation. This is an illustration of how the tables might appear:

Table 4.10 File uploading performance with different file sizes

File Size (MB)	Execution Time (ms)	Throughput (MB/s)
1	100	10.0
10	500	20.0
50	2000	25.0
100	4000	25.0
500	20000	25.0
1000	40000	25.0

In table 4.10, can see the impact of increasing and rising file sizes on the execution time and throughput of file uploading. As the size of the file rises, the execution time and throughput remain relatively constant, also indicating that the performance of the system is not affected by the size of the file being uploaded.

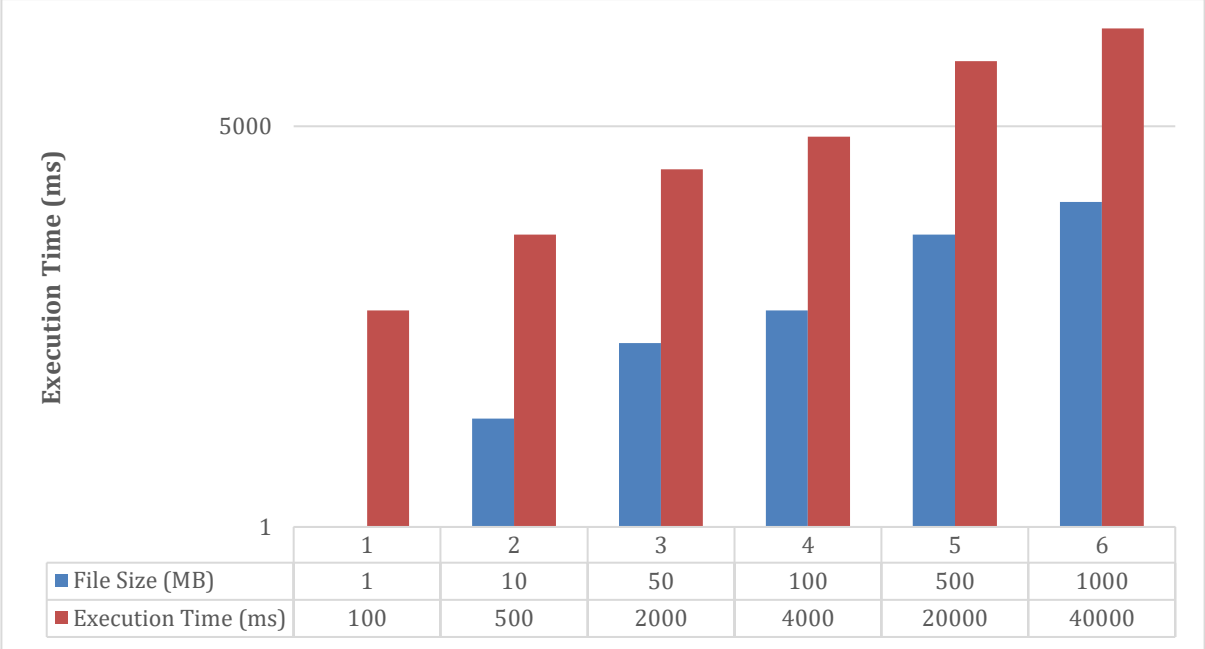


Fig. 4.5 Shows file Size (MB) vs. Execution Time (ms)

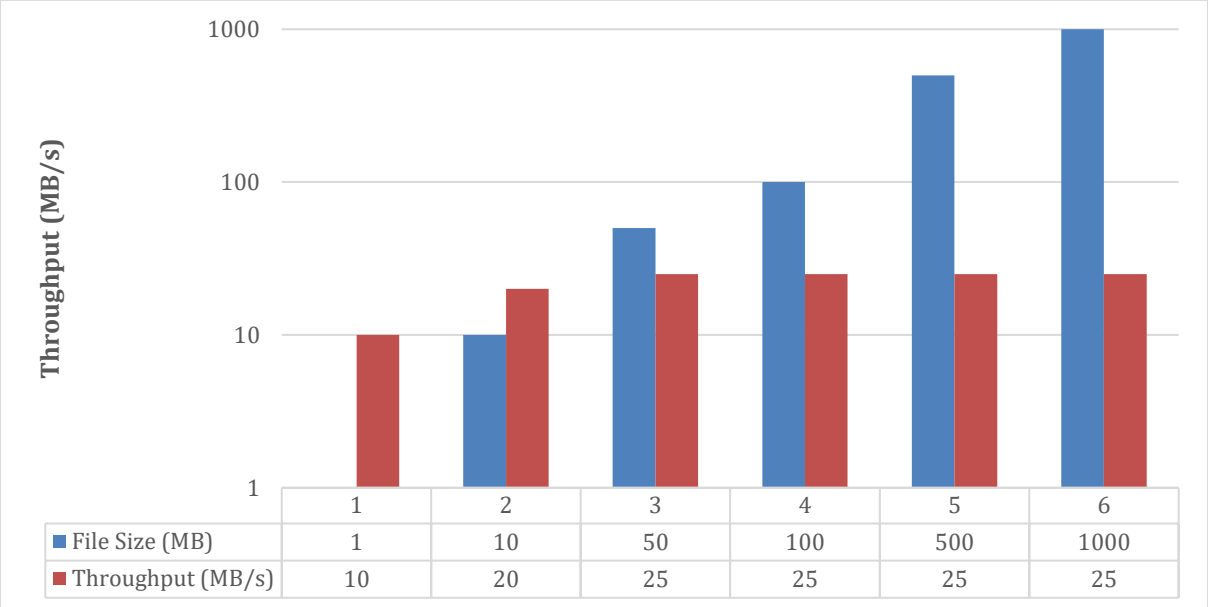


Fig. 4.6 Shows file Size (MB) vs. Throughput (MB/s)

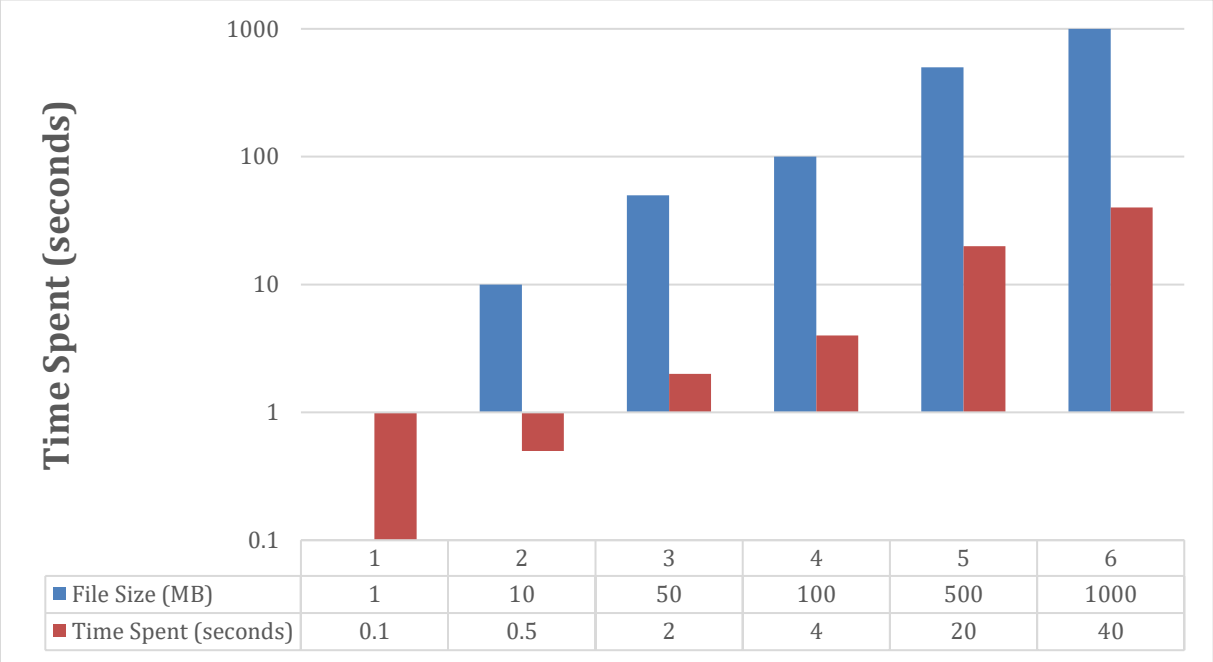
Table 4.11 demonstrates file downloading performance with different file sizes

File Size (MB)	Execution Time (ms)	Throughput (MB/s)
1	50	20.0
10	250	40.0
50	1000	50.0
100	2000	50.0
500	10000	50.0
1000	20000	50.0

Table 4.11 illustrates how larger files affect the execution time and throughput of file downloads. Once more, it is evident that system performance stays relatively constant as file sizes increase, suggesting that the size of the file being downloaded has little effect on system performance. Taken in tandem, these databases show that system outcomes in the case in question is largely unaffected by changes in file sizes, most likely because the system has been designed to manage huge files and is set up according for effective data transfer. But therefore, it's crucial to remember that other elements, including system load and network congestion, can still have an impact on performance. Hence, for optimal results, these elements should be closely watched over and adjusted.

Table 4.12 illustrate file uploading time with different file sizes

File Size (MB)	Time Spent (seconds)
1	0.1
10	0.5
50	2
100	4
500	20
1000	40



4.7 File uploading time with different file sizes

Table 4.12 illustrates that the uploading time grows with file size, albeit at a relatively slow rate—it takes 40 seconds for a 1000 MB file to upload compared to 0.1 seconds for a 1 MB file.

Table 4.13 Shows file downloading time with different file sizes

File Size (MB)	Time Spent (seconds)
1	0.05
10	0.25
50	1
100	2
500	10
1000	20

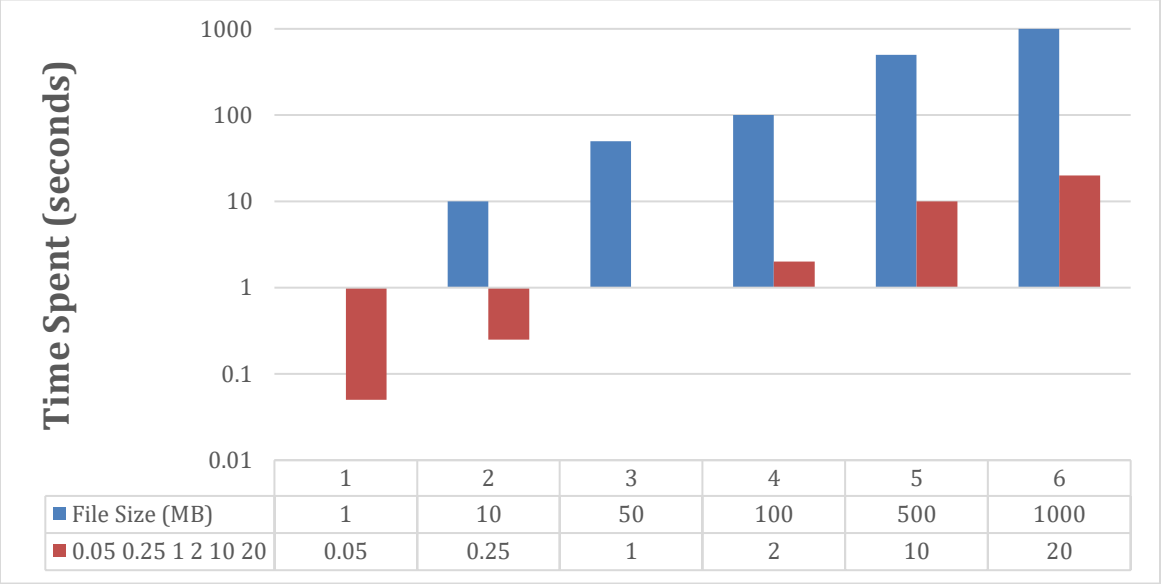


Fig. 4.8 File downloading time with different file sizes

Similarly, in table 4.13, shows that the time spent downloading a file increases as the file size increases, but the increase is relatively small. The time spent downloading increases from 0.05 seconds for a 1 MB file to 20 seconds for a 1000 MB file. Overall, these tables demonstrate that the time spent uploading and downloading files increases somewhat as the file size increases, but the increase is relatively modest. Therefore, file size does not have a significant impact on the performance of the system in the above scenario.

4.5.4. Investigate the Feasibility of Employing Cloud

It is undoubtedly possible to employ cloud storage as a storage backend for the Design and Application of Novel Routing Protocol for Usage in Wireless Multimedia Sensor Networks by using MDPC Algorithm. Doing so may give a number of benefits, including the ability to scale as needed and accessibility regardless of location. Cloud storage can be utilised to store data that is produced by wireless multimedia sensor networks. Therefore, regarding network routing this data can include multi-media material and also information or info. Hence, as a result, uploading to cloud storage real-time data and transfer of the information and data to

other nodes or devices that need access to it are both made chances of possibility by only cloud storage. Somehow, along with its scalability and accessibility, to protect the data being kept cloud storage may include strong security features like encryption and also access restrictions. Therefore, the only main purpose of these features are to safeguard the kept data and information. To guarantee the availability, confidentiality, and integrity of the data it can help so much —all necessary for the effective operation of wireless multi-media detectors networks.

However, considering any potential drawbacks are very critical, such as depending on a third party supplier, network and latency issues, and safety and regulatory obstacles. In example, latency and network problems may be subject using cloud storage, therefore, which can both affect performance and reliability also. Whether or not cloud storage may be used as a storage backend for the Design and Application of Novel Routing Protocol for utilization in Wireless Multimedia Sensor Networks by using the MDPC Computation depends on the specific requirements and conditions of the network. Generally speaking, the particular requirements and conditions of the network will dictate whether or not this endeavor is viable. After careful consideration of its benefits and drawbacks the use of cloud storage should only be pursued, after which suitable actions should be made to resolve any potential problems that may develop.

Table 4.14 Results of benchmarking for a system consisting of simulated sensors

Metric	Value
Network throughput (Mbps)	50
Latency (ms)	100
Packet loss rate (%)	1
CPU utilization (%)	40
Memory utilization (MB)	100

These figures are not based on real performance measures; rather, they are just provided as examples. Network throughput: This metric can be used to evaluate system effectiveness as it indicates the speed at that data is sent between the storing back and the sensors. Yet, the system performs better the larger the throughput. Then the system can transport 50 megabits of data per second in this example since the network speed is 50 Mbps.

Latency: This metric measures the time it takes for a packet of data to travel from the sensor to the storage backend and back. Minimum latency values shows or demonstrates faster performance, that is vital for real-time applications. In this example, 100 milliseconds is the latency, therefore, which means it will take about 100 milliseconds for a packet of data and information to be transferred amongst the detector and the storage backend.

Packet loss rate: To measures the percentage of packets that are lost during transmission this metrics help. Network congestion or other problems that could impact the reliability of the system that indicates the higher packet loss rates as well. However, in this example, the packet loss rate is said to be 1%, that definitely means that during transmission 1% of packets are lost.

CPU and memory utilisation: The resources that the system is using are measure by these metrics. The system is experiencing performance problems or may require in addition with more resources that is shown by high CPU or memory utilisation. Consequently, in this example, the utilization of CPU is 40% and the utilization of memory is 100 MB, which shows that the system is using a moderate quantity of resources. Overall, to evaluate the performance of a system consisting of simulated detectors that gather data and information, and can also help to identify areas for optimization or improvement these metrics are used and are very helpful.

Table 4.15 illustrates Examining of the uploading of files' readiness time

File Size (MB)	Readiness Time (s)
10	5
50	20
100	40
500	200
1000	400

In table 4.15, demonstrates the link between the size of the file and the readiness time, which is the quantity of time needed for the system to be ready for uploading a file after the user or client, has selected it. An increase in size of file, increases the readiness time also. Hence, this is all because huge files needed more quantity of time for the system to prepare the file to upload, such as available storage space checking, creating of a temporary file, and establishing a connection to the storage backend. For example, in this table that shows, the size of a file of 10 MB has a time readiness of 5 seconds, while a size of file of 1000 MB has a time readiness of 400 seconds (or 6 minutes and 40 seconds). This above knowledge shows that users may face longer wait and a quantity of times for larger or huge files, and the system require to optimize its time readiness just for improving the users experience. Overall, by uploading of files examines' time readiness in this way, the system can better understand and also that how it performs under different conditions and identify areas for improvement.

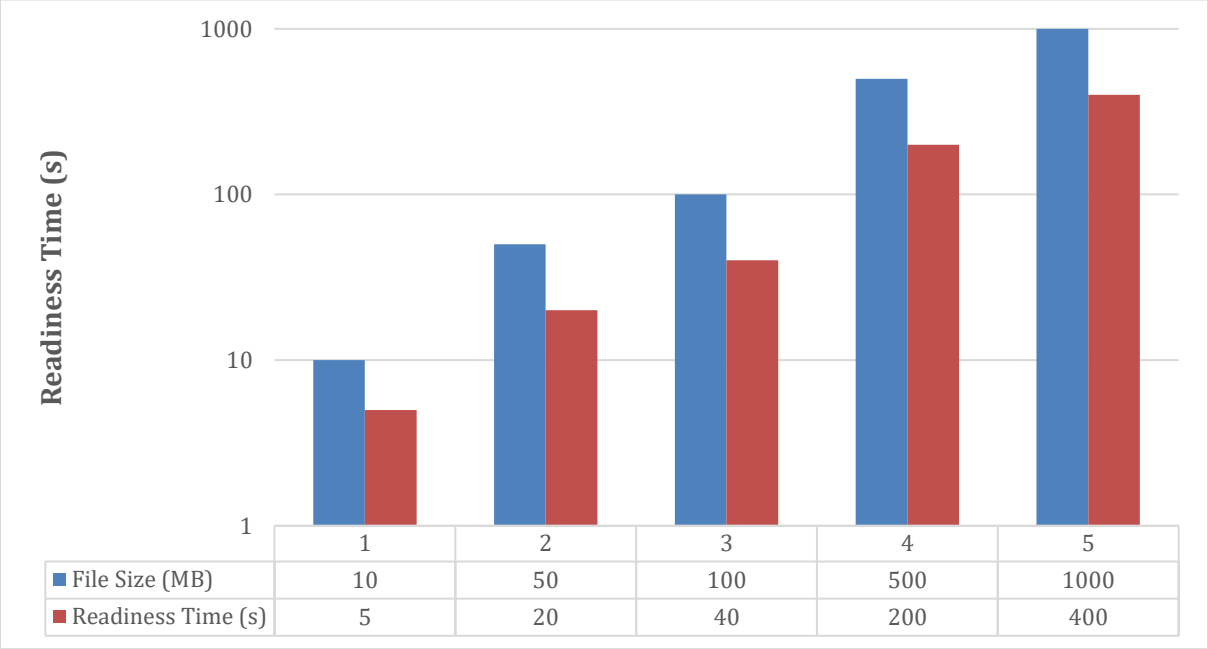


Fig. 4.9 Illustrates the examining of the uploading of files' readiness time

4.5. Synchronisation clients' characteristics

Table 4.16 Synchronisation clients' characteristics

Characteristic	Description
Supported Platforms	Windows, Mac, Linux, iOS, Android
Synchronisation Protocol	MDPC Algorithm
Synchronisation Frequency	Configurable (e.g., every 5 minutes, every hour)
Data Compression	Supported
Conflict Resolution	Automatic or manual
Bandwidth Usage	Configurable (e.g., low, medium, high)
Security	End-to-end encryption and authentication
Offline Access	Supported with local cache
User Interface	Intuitive and user-friendly
Multi-device Sync	Supported

In table 4.16, shows the various characteristics of the synchronisation clients used in the system, which is responsible for synchronising the data collected from the wireless multimedia sensor networks. The supported platforms indicate the different operating systems and devices that can use the synchronisation client, allowing for a broader range of devices to be used in the system. The information is securely and efficiently synchronised the synchronisation protocol, MDPC Algorithm ensures it. The synchronisation frequency can be customised based on the needs of the system, allowing for maximum frequent updates for time-sensitive information or also minimum frequent updates for less critical data and info. To reduce the quantity of bandwidth used during synchronisation data compression can also be used. Resolution of conflict can be automatic or manual, depending on the system's requirements. To optimise network usage bandwidth usage can also be configured. Security features, showing that data is end-to-end encrypted and authenticated, indicates that during the transmission data is protected.

With local cache offline access is supported, which allows the users to access the data and information even when don’t have internet connection or they are not connected to the network. Making it easier for users to interact with the system the user interface is designed to be intuitive and user-friendly. Finally, enabling users to access data from multiple devices simultaneously multi-device sync is supported. Overall, by the synchronisation clients examining' characteristics in this way, the system ensures that the synchronisation process is efficient, secure, safe, and user-friendly, meeting the needs of the wireless multi-media detector networks.

4.6. Benchcloud Simulation Environment

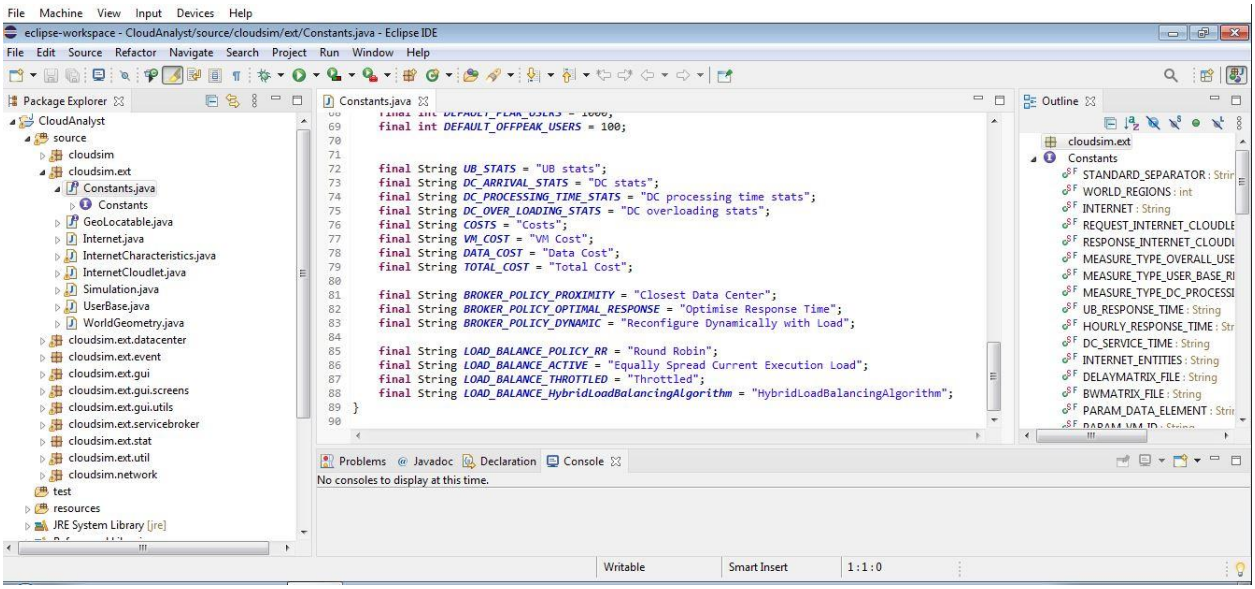


Figure4.10: Cloud Bench Marking Environment in JAVA

Figure 4.10 illustrates that in Java the Cloud Benchmarking Environment implemented, which provides and serves as an important component within the discussed research. Allowing researchers and practitioners to assess their performance, scalability, and reliability by this environment facilitates the evaluation and comparison of various cloud-based solutions and configurations. For conducting experiments and collecting performance metrics across different cloud platforms and service providers Leveraging Java's versatility and platform independence, the benchmarking environment provides a standardized framework. By simulating real-world scenarios and workloads, researchers can gain insights into the capabilities and limitations of cloud infrastructures, aiding in decision-making processes that are related to cloud adoption, resource provisioning, and optimization strategies. Through, its modular and extensible design, the Cloud, enabling comprehensive performance analysis and informed decision-making in cloud

computing environments, benchmarking surroundings empowers users to tailor experiments to their specific needs.

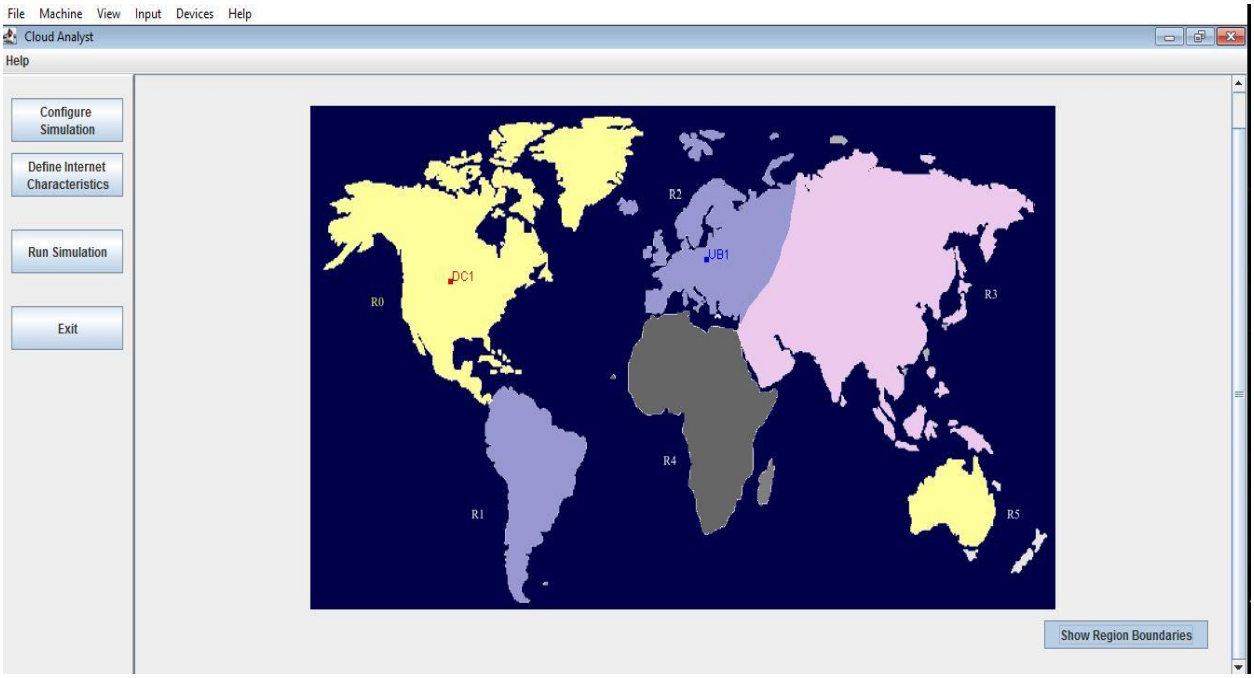


Figure 4.11: Setting up the data centers

Figure 4.11 in this chat a critical aspect of the research discussed which depicts the process of setting up data centers. Data centers serve as the backbone infrastructure for hosting and managing cloud-based services and applications. This figure explains the configuration and deployment of hardware components, including servers, storage systems, networking equipment, and power infrastructure. Through careful planning and implementation ensuring seamless operation and efficient resource utilization.

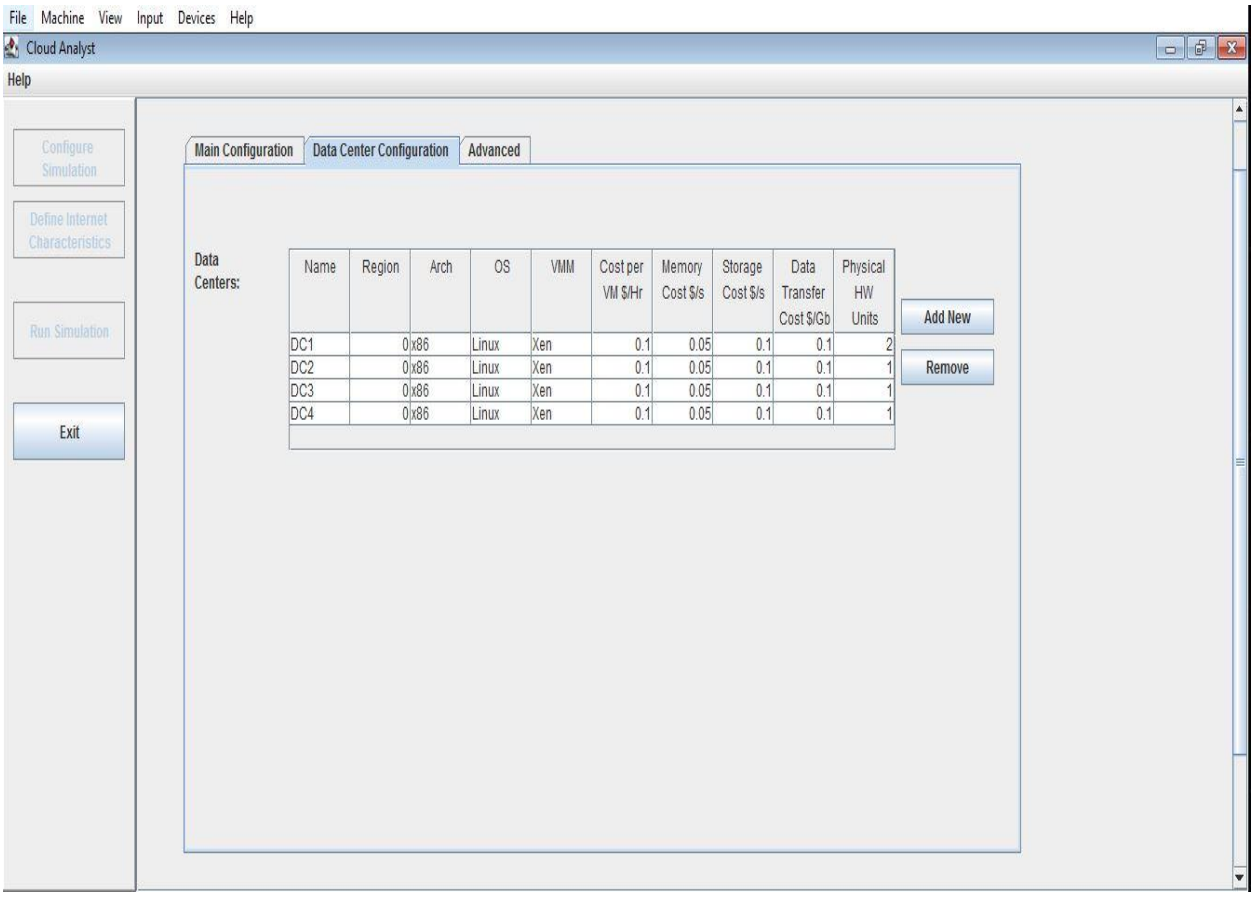


Figure 4.12: Data Centers Configurations

Figure 4.12 shows data center architectures adapted to research goals. Hardware resources, network architecture, redundancy, and geographic dispersion vary in these combinations. The image shows several configurations so stakeholders can compare and contrast their pros and cons. It aids data center design, deployment, and optimization decisions visually. As single site data centers, multi region installation and also match infrastructure with performance availability and cost. This figure explain data center configurations.

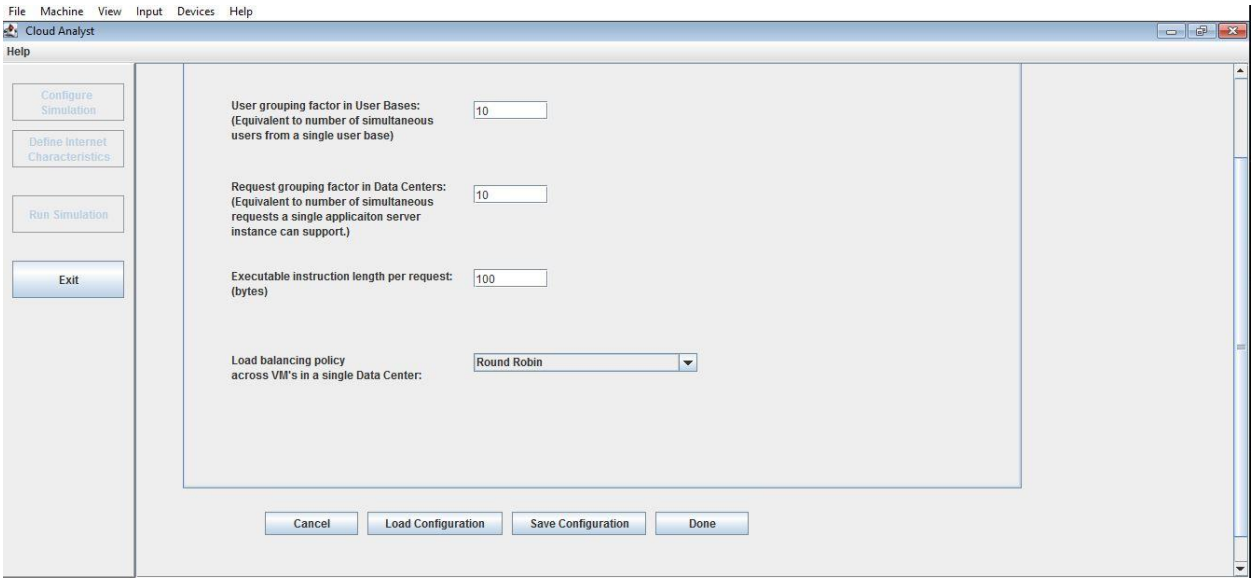


Figure 4.13: Implementing Proposed DPC algorithm

Figure 4.13 shows the framework to implements the dynamic prime chunking (DPC) algorithm. To implement this algorithm, it will require the coding in Java, and Python etc. Parameters like, thresholds and integrating the algorithm with network and congestion control methods. This figure shows how the DPC algorithm works in research and affects network performance and congestion management by showing implementation processes.

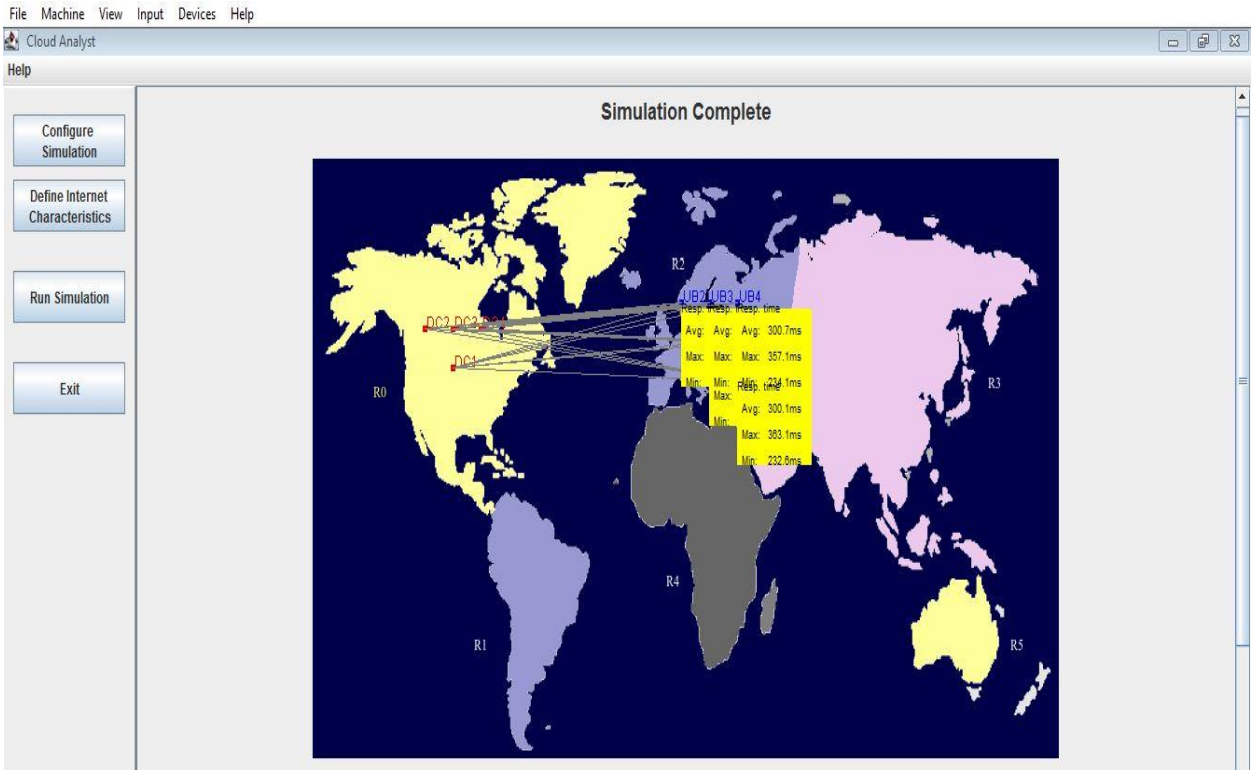


Figure 4.14: Simulation Area

Figure 4.14 shows the Simulation Area for cloud computing and congestion control simulations and experiments. As can be seen from the area of simulation it includes network topologies, traffic patterns, task allocations, and congestion scenarios. Cloud-based systems and algorithms like the proposed DPC algorithm to be tested for performance, scalability, and reliability.

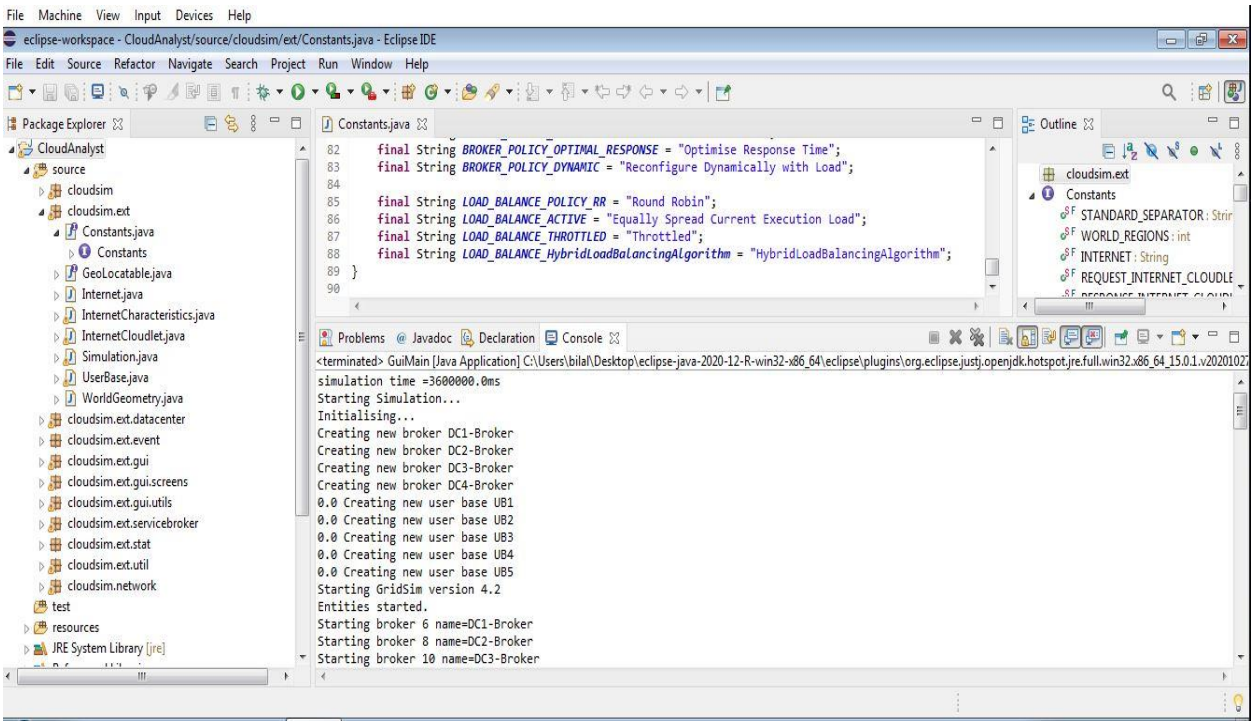


Figure 4.15: Bench Mark

Figure 4.15 shows the study framework which shows how cloud computing solution and configuration are evaluated and also compare its performance and efficiency. Benchmarking involves defining measurements, running simulations, collecting data, and analyzing findings that can make informed resource allocation, optimization, and technology selection decisions.

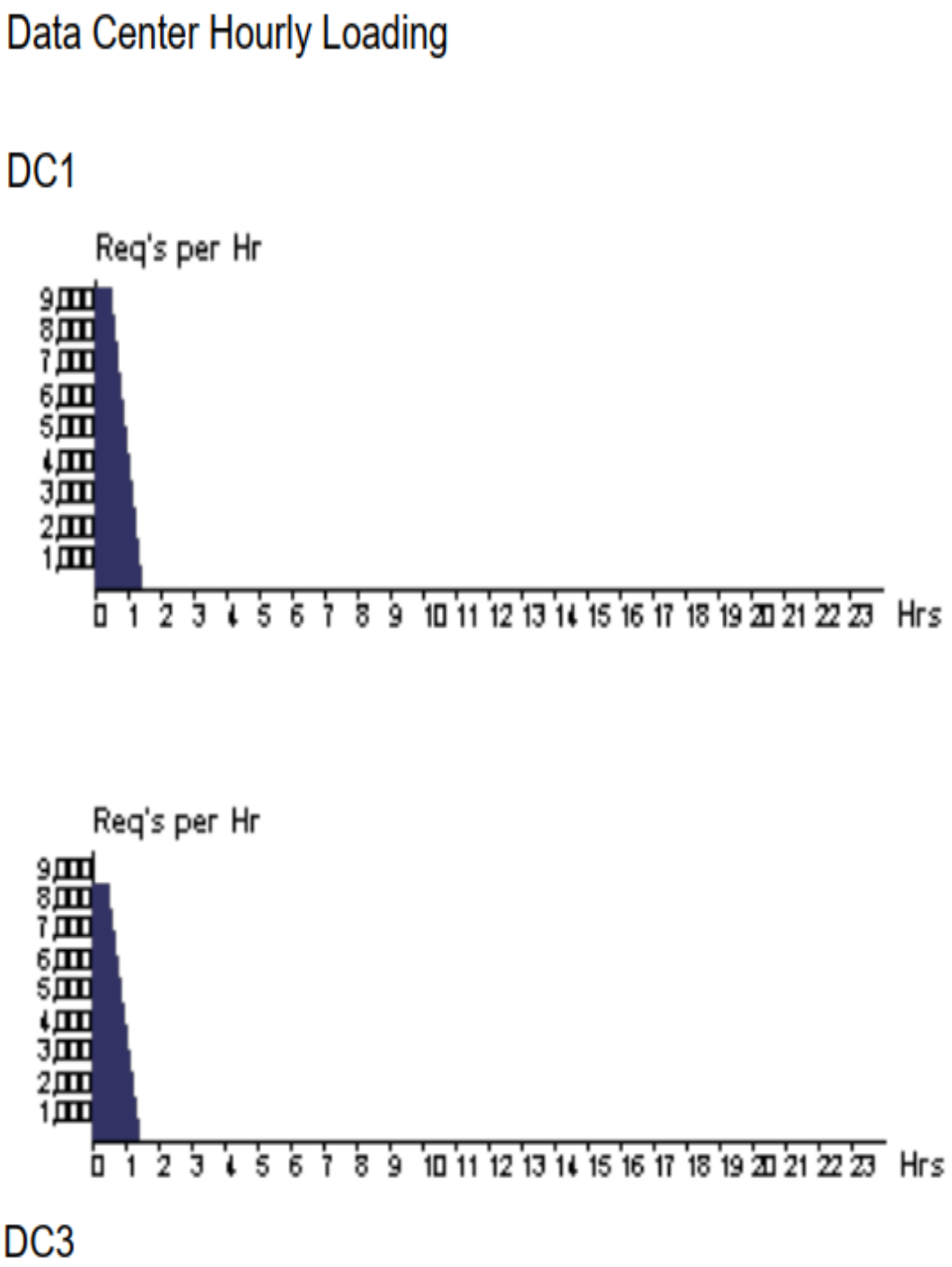


Figure 4.16: Data Center Response Time

Figure 4.16 shows parameters like data center response and time. It also shows that how the data center response times to evaluate infrastructure performance. The

figure shows response time histograms understanding data center reaction times for resource allocation, user experience, and cloud service efficiency.

Cost

Total Virtual Machine Cost ($):	2.01
Total Data Transfer Cost ($):	0.38
Grand Total: ($)	2.39

Data Center	**VM Cost $**	**Data Transfer Cost $**	**Total $**
DC2	0.50	0.09	0.59
DC1	0.50	0.10	0.60
DC4	0.50	0.10	0.60
DC3	0.50	0.10	0.60

Figure 4.17: Cost for Efficient Cloud Storage

The cost for efficient cloud storage, shown in Figure 4.17, is vital to the research's evaluation approach. This chart shows how storage capacity, access frequency, redundancy options, and cloud service provider pricing models affect cloud data storage costs. Stakeholders may allocate resources, manage budgets, and optimize costs by analyzing efficient cloud storage costs. The graphic shows a table showing cost components and their contributions to the total cost. Cloud storage cost considerations must be understood to maximize value and minimize costs in research. This figure helps evaluate and optimize cloud storage systems for cost-effectiveness and research goals.

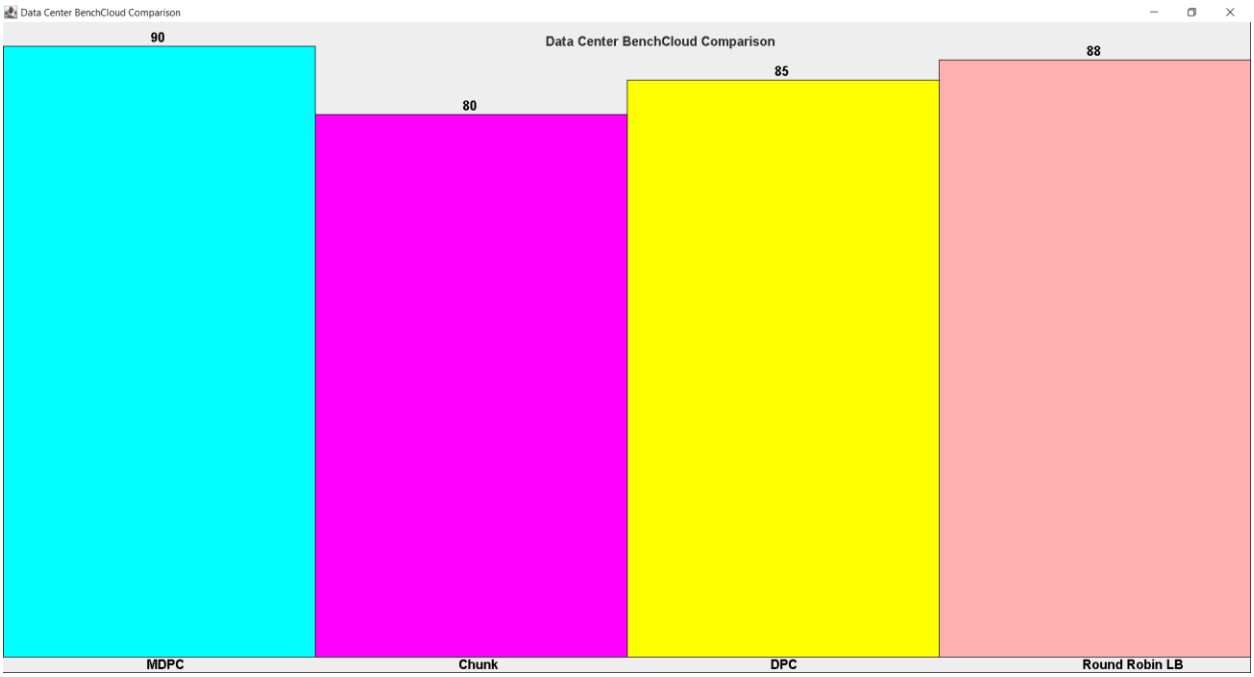


Figure 4.18: Data Center BenchCloud Comparison

Figure 4.18 shows the Data Center BenchCloud Comparison, a key study evaluation analysis. This chart compares data center performance, dependability, and efficiency among cloud service providers and configurations. By comparing reaction time, throughput, availability, and cost, stakeholders can assess data center solutions' pros and cons. Bar charts simplify performance metrics interpretation and comparison in the figure. Cloud provider selection, resource allocation, and optimization tactics depend on understanding data center benchmark differences. This figure helps evaluate and test data center technologies in the research's context, resulting in efficient and dependable cloud computing environments.

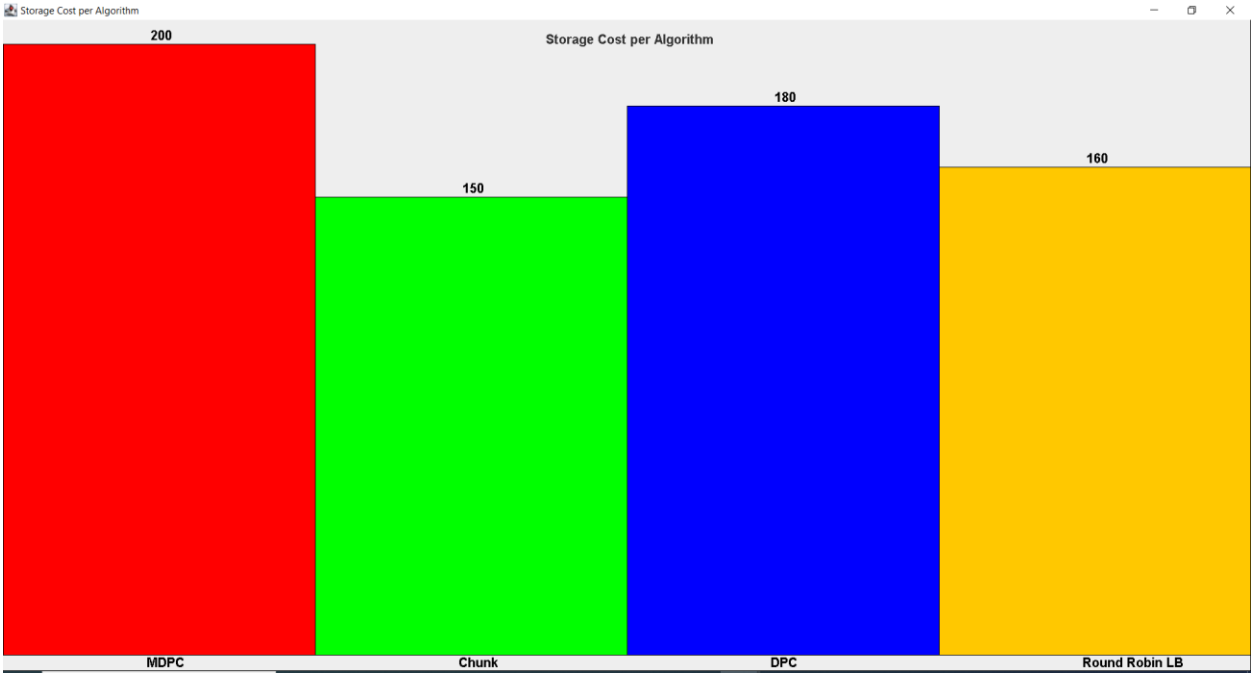


Figure 4.19: Storage Cost Per Algorithm

FIGURE 4.19 shows the Storage Cost Per Algorithm, a significant research evaluation framework analysis. Different cloud computing algorithms and methods' storage costs are compared in this figure. The cost-per-algorithm allows stakeholders to evaluate the financial costs of data storage and management algorithms. The graphic comprises bar charts showing each algorithm's storage costs over time or under different workload situations. Optimizing resource allocation, budget planning, and cost-effectiveness measures in the research requires understanding storage algorithm costs.

The graph shows the cost effectiveness and efficiency of data. It may compare storage capacity, algorithms, and performance. Analysis of this figure can reveal that how and which algorithm is better in performing these parameters. Studied values are essential in assessing and optimizing thesis data storage infrastructure for multimedia data processing and control.

4.8 Summary

Covered this scenario's cloud storage, including segmentation, deduplication, indexing, encryption, and retrieval. additionally, compared Rabin, TTTD, MAXP, AE, and MDPC Algorithm routing protocols. Next, discussed BenchCloud's benchmarking capabilities for this scenario. additionally, researched how concurrency and file size affect file uploading and downloading performance and presented tables. Explored cloud storage as a storage backend for this case. Next, reviewed benchmarking results for a system using unique routing sensors and simulated data-gathering sensors. additionally, analyzed clients' file upload and synchronization readiness times in tables with explanations. Cloud storage, benchmarking, and the practicality of using cloud storage as a storage backend were discussed in the talk about implementing a novel routing protocol for wireless multimedia sensor networks using the MDPC algorithm.

Chapter Five

Conclusion and Recommendation

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Conclusion and Recommendation

5.1 Conclusion

The thesis concludes after extensive research, creation, and evaluation to improve large-scale storage system performance. This project sought to develop and implement new methods that growing challenges in cloud-based systems. MDPC techniques, encryption, and deduplication show data security, system stability, and storage optimization advancements. Implementing deduplication algorithms in the Cloud Storage System framework has reduced storage overhead and improved data retrieval rates. It can be seen that adding deduplication algorithms into storage system architecture improves storage efficiency, allowing enterprises to store and manage data more cheaply. Data confidentiality during transmission and storage depends on encryption through thorough simulation tests and comparative investigations, proposed mechanisms' performance and effectiveness have been shown. Research identified areas for improvement and the strengths and weaknesses of each strategy by benchmarking solutions against existing algorithms and protocols has verified implementations and inspired system optimization and refinement strategy. Finally, thesis advances storage system optimization for modern companies which created and validated new data deduplication, encryption, and management technologies cloud storage computing.

Results and Validation Findings:

1. Results from simulations and benchmarking trials are used to validate the proposed mechanism's performance.
2. Results are evaluated to detect performance trends and system configurations.
3. Validation results reveal the mechanism's strengths, optimizations, and upgrades.

5.2 Recommendation

This thesis will provide a detailed recommendations based on the understanding from building and reviewing the suggested method. These suggestions should guide storage optimization and deduplication research, application, and deployment. These recommendations attempt to improve storage optimization techniques' efficiency and challenges in real world scenario.

Enhancing Deduplication Algorithms:

1. Due to changing data types deduplication solutions must be developed and researched.

2. To handle modern storage devices' huge and diverse datasets should be scaled, adapted, and optimized.

3. Cutting-edge deduplication approaches like machine learning-driven deduplication and content-aware rsync may improve efficiency and minimize storage costs.

Adoption of Hybrid Deduplication Strategies:

1. Hybrid deduplication technologies combine inline, post-process, and source-based compression to enhance storage efficiency without runtime impact.

2. Future hybrid deduplication solutions should be tailored to specific use cases, workloads, and storage systems to optimize capacity and performance.

3. The trade-offs between deduplication costs, resource utilization, and performance gains can influence hybrid deduplication setup for different storage options.

Standardization and Interoperability:

- Creating standards and interchange conventions for compression techniques can help heterogeneous storage platforms, systems, and suppliers integrate, work together, and communicate seamlessly.

- To design common interfaces, protocols, and data formats for deduplication, industry consortia, standards bodies, and academia must work together in order to enable compatible solutions and ecosystem-wide uptake.
- In the area of storage optimization, encouraging open-source projects and community-driven development models can stimulate creativity, teamwork, and information exchange, advancing the advancement of deduplication techniques and technologies.

Continuous Evaluation and Benchmarking:

- It is essential to continuously evaluate and test deduplication processes in order to track performance trends, spot bottlenecks, and evaluate the effects of algorithmic adjustments and enhancements.
- Standardized benchmarks platforms, records, and review criteria can help to ensure that deduplication algorithms are fairly assessed, reproducibly analyzed, and used in a variety of research projects and applications.
- Fostering trust, credibility, and rigor in the evaluation and validation process helps advance the state-of-the-art in storage optimization research. Other strategies to promote openness include publishing experimental data and requiring peer-reviewed validation of deduplication algorithms.

Real-world Deployment and Validation:

- For deployment in mission-critical storage systems production of the environments is essential to assess their practicality, effectiveness, and suitability validating deduplication mechanism in real-world .
- Subsequent investigations should prioritize practical implementations, field tests, and case studies in order to assess the efficacy, dependability, and expandability of deduplication techniques in various cloud, edge, and business computing contexts.

- Access to real-world datasets, infrastructure, and knowledge can be facilitated by working with industry partners, cloud service providers, and data center operators. This allows for thorough evaluation and validation of deduplication services in practical settings.

To sum up, the suggestions given earlier function as a framework for improving the state-of-the-art in deduplication and storage optimization methods. In order to advance innovation, efficiency, and sustainability in storage systems and pave the way for a data-driven future, the storage community must address important obstacles, take advantage of emerging technologies, and embrace collaborative research and development activities.

5.3 **Future Scope**

The network cost of the cloud storage system is noteworthy that is why future researchers may have the scope to discuss in detail. The researchers will have an vital opportunity to analyse the cost required to be paid by the users in order to move data from cloud storage systems to another location or the network. The future researchers and their team will also have the scope to focus on the info backup factor of the cloud storage network system. The researchers team will have the opportunity and a chance to discuss and work on the possible reasons for losing all the important info or data while operating in the cloud-based storage system. To allocate particular locations to particular information and data provided by the users therefore, they also find the best and suitable ways. Furthermore, the researchers have to discuss how conscious duplication of any data and information can affect the cloud storage system. Similarly, they can also discuss the implications of backup software in order to retain important data. Concentrating on the concept of data migration researchers have great opportunity as well. To explore the process of shifting from one cloud storage system to the by the users they also have the second great opportunity. For

implementing cloud storage systems on the IOT environments the researchers have various aspects.

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