COMPARISON ON SCHEDULING ALGORITHM IN APACHE HADOOP

By

YASIR ADIL MUKHLIF

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This is to certify that we have read this thesis and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Science.

Academic Title Name SURNAME	Asst. Prof.Dr. Sefer KURNAZ
Co-Supervisor	Supervisor

Examining Committee Members (first name belongs to the chairperson of the jury and the second name belongs to supervisor)

Prof. Dr. Osman Nuri UÇAN	Graduate School of Science and Engineering, Altınbaş Üniversitesi	_____
Asst. Prof. Dr. Sefer KURNAZ	Graduate School of Science and Engineering, Altınbaş Üniversitesi	_____
Prof. Dr. Adem KARAHOCA	Faculty of Engineering and Natural Sciences, Bahçeşehir University	_____

I certify that this thesis satisfies all the requirements as a thesis for the degree of Master of Science.

Asst. Prof. Dr. Çağatay AYDIN

Head of Department

Approval Date of Graduate School of Science and Engineering: ____/____/____

Prof. Dr. Oğuz BAYAT

Director

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Yasir Adil MUKHLIF

DEDICATION

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ABSTRACT

COMPARISON OF SCHEDULING ALGORITHM IN APACHE HADOOP

MUKHLIF, Yasir Adil

M.S., Computer Engineering, Altınbaş University,

Supervisor: Asst. Prof. Dr. Sefer KURNAZ

Co-Supervisor:

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Recently, big data has become one of the important parts of computer engineering. The data goes rapidly increase on our planet it can generate from different kinds of sources, for instance, astronomy, oceanography, healthcare, social media, banking, manufacturing, and many others. However, scheduling considered one of the utmost important parts in Apache Hadoop. Indeed, it needs more study to try to cover it. However, this study is critically classify, for other studies, it is compare, investigate and analyze the result by using systematic literature Review (SLR) methodology. Moreover, it identifies the pros and cons an individually for each scheduler algorithm that selected to make this study. Plus, this thesis covered which mechanisms are being used in the algorithms and which scheduler algorithm dominantly used in Apache Hadoop compare to the others scheduler algorithms it used. Thus, these things were not covered in another study in the literature on computer engineering.

Keywords: Job scheduling, Scheduler algorithms in Big Data, Apache Hadoop job scheduler Big Data job scheduler, FIFO scheduler Fair scheduler

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LIST OF ABBREVIATION

AM	Application Master
ANN	Artificial Neural Networks
CLARANS	Clustering Large Applications based upon Randomized Search
DAS	Direct-Attached Storage
DW	Data Warehouse
FIFO	First In First Out
GPU	Graphics Processing Unit
HDDS	Hard Disk Drives
HDFS	Hadoop Distributed File System
HPC	High Performance Computing
LATE	Longest Approximate Time to End
LHC	Large Hadron Collider
LLE	Locally Linear Embedding
LSST	Large Synoptic Survey Telescope
MPP	Massively Parallel Processing
NAS	Network Attached Storage
NCCS	NASA Centre for Climate Simulation
NIH	National Institutes of Health
NITRD	Networking Information Technology Research and Development
NM	Node Manager
NSF	National Science Foundation
PCA	Principal Component Analysis

PCAST	President’s Council of Advisors on Science and Technology
PCM	Phase Change Memory
RDBMS	Relational DataBase Management System
SAN	Storage Area Network
SLAS	Service Level Agreements
SLR	Systematic Literature Review
SNA	Social Network Analysis
SQL	Standard Query Language
SSD	Solid State Drive
SVM	Support Vector Machines
UDFS	User Defined Functions
WSNS	Wireless Sensor Networks
YARN	Yet Another Resource Negotiator

1. INTRODUCTION

1.1 BIG DATA

Big data has just become a major topic recently [1, 2], bearing certain resemblance to traditional database systems and, yet being much larger and having higher processing capacity. Big data is simply large, quick in motion and bears not just structured, but unstructured patterns. In comparison, traditional databases merely encompass structured patterns [1, 3, 4]. In order to make the most of this concept, other options are to be employed for data processing. Big data covers data with additional processing capacity compared to common database systems[5], and hence serves a major function, while gaining popularity, in different fields such as computer science and technology, business and finance, banking and online sales, oceanography, astronomy, healthcare and many others [6]. Currently, big data is a must in business applications and numerous other disciplines[2] as it offers extensive advantages. The concept covers a large array of datasets, whose dimensions keep on growing on a daily basis since data is added as such and generated by countless factors like social media, business transactions, personal data, digital photos, and others. Big data conveys large and undesired data of different nature, structured and unstructured[7]. In the first case, the data is kept systematically and with proper definitions, whereas in the latter, it is simply not organized and remains free of definition [8].

An example of unstructured data is that from Wikipedia, Google, and Facebook, and those with structure cover data from E-transactions as an example [9]. Given this dual characteristics, certain obstacles on the way of big data may prevail, namely data capture, sharing, privacy, transfer, analysis, storage, search, job scheduling, handling of data, visualization, and fault tolerance [10]. Naturally, tackling these obstacles can be rather hard if one is to apply common database management approaches[4], those that lack processing, analyzing, and scheduling properties for such extended data[11]. For this reason, an alternative has to be put in place[12], for instance Hadoop, an applicable instrument to deal with such obstacles and difficulties. As an open-source tool to manage, Hadoop was set up by Apache[13] and it is able to manage extensive data, even in

terms of petabytes. This is a cloud platform with extreme reliability to guarantee extended data availability through the use of numerous copies at different nodes[14]. There is the benefit of scalability, with bugs also being sought and managed [15]. Two components establish Hadoop; namely HDFS and MapReduce[16, 17]. The Hadoop-distributed file system can be applied to save data, with MapRedcue reduce employed to process it. The latter serves two purposes: Map and Reduce, as the terms implies[11], both written by users and assuming values in the form of input key value pairs to release the output result again in the form of key value pairs. Initially, the Map generates intermediate key value pairs, and later the MapReduce function integrates those values sharing identical key like a library. Eventually, the key proceeds into the Reduce function, which takes it along with a set of values to be combined into a tinier set. Job scheduling makes processing faster and minimizes the response time with the help of improved methods based on the jobs, as well as an ideal use of resources[18]. FIFO scheduling is a form of default scheduling within Hadoop where the tasks entering initially are assigned first order compared to the ones arriving next.[17, 19, 20]. Sometimes, such scheduling may cause trouble, though, if more extensive tasks are arranged before less extensive ones, thus causing starvation[21]. In this respect, fair scheduling allocates equal resources to all tasks.

Yahoo first proposed Capacity scheduling to increase the use of sources and throughput among clusters. LATE scheduling policy improves the functioning of jobs and decreases response time through identifying sluggish processes in a cluster and starting equal ones in the background. Facebook applies Delay scheduling to improve the functions and reduce response time in map jobs through modifications in MapReduce. Deadline scheduler, deadline limits are identified prior to job scheduling so as to maximize the use of system. Resource-aware scheduling makes resource use better. By applying a node, master node, and worked node to finish the tasks. Matchmaking scheduling signals each node using a location indicator to guarantee a fair share in capturing a local task for each[22]. In this way, better data locality and cluster use can be attained. In the field of big data processing, some articles exist on the topic of job scheduling algorithms.

1.2 PURPOSE OF THE STUDY

This study will critically classify, compare and investigate about different scheduler algorithm in the Apache Hadoop framework. Furthermore, it identifies the scheduler in which manner can be used whether can be heterogeneous or homogeneous. In additional, the study discuss the several types of optimization of scheduling algorithm that can be improve the performance and less usage of utilization of scheduling of apache Hadoop. To reach our goal, systematic literature review (SLR) it was the methodology that is used to collect information and analyses from a different point of views. Therefore, the thesis can be a comprehensive survey on the scheduling algorithms used in Apache Hadoop.

1.3 SIGNIFICANCE OF THIS STUDY

The scheduling algorithm is one of the basic technologies of Hadoop platform, its primary function is to manage the order of job execution and assign the user's job to execute upon resources. Familiar with that Hadoop is a general purpose that empower high-performance processing of data over a set of distributed nodes. The topic still hot and required explanation in a different issue that affecting on a scheduling algorithm. Consequently, in this thesis, we opted Apache Hadoop as a case for this study to cover all algorithm it is used for scheduling task.

2. METHTODOLOGY

2.1 RESEARCH METHODOLOGY

The aim of this study is to classify, compare and explore detailed information about different schedulers used in Big Data frameworks in addition to highlighting the weakness and strengths of each schedule in different use cases. Because of that, we use the systematic literature review (SLR) methodology, which is interpreting and evaluating research related to any given topic. A systematic literature review is entirely based on secondary studies, such as scholarly articles, research papers, and published theses. The main reason for this selection is that there is a large amount of information about Big Data scheduling which needs to be collected, analyzed, and eventually interpreted in a way as to provide compelling results for the present work.

2.2 THE SELECTION OF A RESEARCH APPROACH

There are different types of research in the literature review all of which can be divided into two types: namely deductive and inductive. The first one is entirely based on the previous theories and hypothesis; whereas the second one is based on non-statistical techniques, which means developing new models and theories. Therefore, we opted for the deductive method as the aim is to get all available insights about scheduling in Big Data[23].

2.3 RESEARCH METHODS

Despite the existence of numerous research methods for the purpose of categorization, the quantitative and qualitative approaches are the widely ones, with the difference originating from the main principles in the research process. The qualitative method is used to gather non-numerical data about a topic, and also the main idea is to check all data collected with the help of textual analysis techniques. Quantitative, in another hand, involves gathering numerical data and checks these data that collected by using statistical techniques. For the purpose of this thesis, the qualitative

method is preferred as it is the most appropriate one for gathering secondary data (scholarly articles, research papers, and published thesis) and checking through thematic analysis [23-25].

2.4 RESEARCH STRATEGY

Research strategy is a plan that gives direction to efforts and thoughts, enabling researchers to perform systematically. In order to do so, the literature review should follow these steps:

- Formulation of the research question
- Use of keywords for the search
- Setting inclusion or exclusion criteria
- Making quality assessment of papers
- Execution of the methodology

2.4.1 Formulation of the Research Question

Research questions should reflect the main goal of the systematic literature review and cover all aspects of the defined goals. These questions are formulated in the following way:

1. In which environment scheduler can be work good?
2. Which type of mechanisms are being used for each algorithm in Apache Hadoop scheduler? Which one's dominantly using?
3. What are the main advantages and disadvantages of different schedulers on Big Data frameworks?
4. What type of scheduling optimizations offered in literature?

2.4.2 Use of Keywords for the Search

To conduct a systematic literature review, we need to research about the papers that are relevant to the topic. Therefore, keyword selection is a significant step in research because the quality of the results is directly related to the keywords being picked in the first place. These are carefully selected terms, and the following are the keywords that were used for conducting the research in this study:

- Job scheduling
- Scheduler algorithms in Big Data
- Apache Hadoop job scheduler
- Big Data job scheduler
- FIFO scheduler
- Fair scheduler
- Capacity scheduler
- Delay scheduler
- Context scheduler
- Deadline constraint scheduler
- Resource aware scheduler
- Matchmaking scheduler
- Enhanced Self adaptive MapReduce scheduler
- Self-Adaptive reduce scheduler
- COSHH scheduler
- Longest approximate time to End scheduler
- Maestro scheduler
- Hybrid scheduler

In Table 1.1, we selected the database that is used for searching in order to identify relevant articles:

Table 1.1: Selected Databases

Database	**Location**
Google Scholar	*https://scholar.google.com.tr/*

IEEE Xplore	*http://ieeexplore.ieee.org/Xplore/home.jsp*
Science Direct	*http://www.sciencedirect.com/*
ACM DigitalLibrary	*http://dl.acm.org/*
CiteSeerX	http://citeseerx.ist.psu.edu/index

2.4.3 Setting Inclusion or Exclusion Criteria

Exclusion and inclusion criteria make filtering possible for the papers retrieved from databases to find the most relevant ones. According to the research questions, the exclusion and inclusion criteria in Table 2 are applied to the selected papers [26]. During this stage, the search in well-defined sources should be performed and the obtained studies should be evaluated in accordance with the established criteria. After executing the search on the marked sources, we obtained a collection of about 335 results clarified by the inclusion criteria. The studies were further filtered to yield 79 primary proposals.

Table 2.1: Inclusion and Exclusion Criteria

Inclusion Criteria
1. Studies scheduling algorithm in Big Data. *2. Journal and/or conference papers.* *3.* Studies *that describe scheduling algorithm in the Big Data frameworks.* *4. Primary or secondary studies.*
Exclusion Criteria
1. Studies not accessible in full text. *2. Studies that do not related to scheduling algorithm in Big Data.* *3. Studies not presented in English.* *4. Prefaces, slides, panels, editorials or tutorials.* *5. Studies that do not answer the research questions.* *6. Duplicated studies such as those published in other papers. In such as case; we included the most recent one.*

2.4.4 Making Quality Assessment of Papers

Quality assessment plays a vital role in SLR and aims to guarantee the relevant papers in terms of properly qualifying to address the related questions used in the study. For each paper included in this study, these criteria are to be deployed [24, 26]:

1. Are the objectives of the research clearly stated?

2. Did search strategy cover an adequate number of years?

3. Did the authors describe a search strategy that was comprehensive?

4. Do the researchers present sufficient data that can support their interpretations and conclusions?

5. Is the method of analysis appropriate and adequately explicated?

3. BACKGROUND OF BIG DATA

3.1 INTRODUCTION OF BIG DATA

Big data compiles large and complicated datasets to also cover management capabilities, social media analytics and real-time data in mass amounts. Here, the analytics aspect simply analyzes data in such large amounts, which may include heterogeneous digital data. Big data addresses volumetric sums measured in terabytes or petabytes – hence the term "big data". Next is the issue of Big Data analytics, where the difficulties mainly lie in capturing, analysis, storage, searching, sharing, visualization, transferring and privacy-related issues. In this respect, conventional SQL attempts or relational database management system (RDBMS) for saving are not practical solutions. Still, a large group of measureable database instruments and methods has come to the surface for these purposes.

In this respect, Hadoop is one of the open-source data-processing tools considered as a safe and sound solution to the problem. The NoSQL is a non-relational database similar to MongoDB in Apache Hadoop. One may define Big Data as any group of data not manageable, or even storable in some occasions, with just one system in order to satisfy the needs as per the service level agreements (SLAs). This description in its second half is vital as one may in effect process any amount of data using one system, where even data not storable given the machine capacity nay be transferred by reading it from shared sources like network attached storage (NAS) mediums. Nevertheless, the duration required to do so would be excessive given the allocated time to do such operations Take the following example: once the estimated job completed at a unit is 200 GB, one may be able read roughly 50 MB per second. Assuming a 50 MB per second flow, 2 seconds are required for 100 MB to be read from the source, thereby roughly an hour for 200 GB. At this stage, let us think the data is to be processed in less than five minutes. With 200 GB needed per job fairly divided among 100 nodes, each managing their own data minus the time for CPU operation and assembly for the results coming from these nodes, the whole operation should take less than a

minute in this way. This easy illustration proves that Big Data heavily relies on the context as per the business requirements.

3.2 BIG DATA IN SCIENTIFIC RESEARCH

For long, numerous aspects of science have been driven by data as computer technology advances. Among these, astronomy, meteorology, social computing, bioinformatics and computational biology rely heavily upon data-loaded findings in large quantities and different forms. To provide an example, an advanced telescope is nothing but a big digital camera to provide numerous pictures from the outer space. The Large Synoptic Survey Telescope (LSST), among these telescopes, can capture 30 trillion bytes of image data in just 24 hours whose data equals in size that of two complete Sloan Digital Sky Surveys every day. Space scientists use such applications and developed techniques in processing to learn more about the beginnings of cosmos. Another example, the Large Hadron Collider (LHC), speeds up particles to create 60 terabytes of data on a daily basis with a pattern that provides unexpected insight into the universe. An estimated 32 petabytes of weather-related simulations and investigations are saved in the supercomputing cluster of NASA Centre for Climate Simulation (NCCS). The information related to human genes is also massive, to the point that first decoding attempts lasted 10 years of processing.

In other cases, numerous projects have been suggested or are in progress in environmental studies, oceanography, geology, biology, and sociology. All of these share the need to create large amounts of data needing automated analysis. Furthermore, a centralized repository is needed because one may not simply duplicate samples for those in distant locations. Henceforth, centralized saving and analysis is key to all system designs.

3.3 BIG DATA OPPORTUNITIES AND CHALLENGES

3.3.1 Opportunity

Lately, numerous government agencies in the United States, namely the National Institutes of Health(NIH) and the National Science Foundation (NSF), have announced that Big Data advantages in making decisions are key to their future initiatives [1], thus their attempt to improve

this technology to facilitate operations upon the approval of massive-scale Big Data initiatives by the government. This move helps to develop new facilities to use knowledge and, in this way, improve the decisions made. According to the Networking Information Technology Research and Development (NITRD) program, lately approved by the President's Council of Advisors on Science and Technology (PCAST), it has been determined that the connection between Big Data and knowledge embedded within such data are a national priority in certain fields. The move can also provide the foundation for additional activities, namely foundation works, creating interest groups, and also ways to deal with complicated data-related issues in sciences and engineering. In the end, all such initiatives will be applied to offer their benefits to the public. As a McKinsey institute report states, proper application of Big Data can have major advantages in changing economies and offering alternative ways for productive development. Using precious knowledge beyond Big Data will turn into a topic of competition in present-day ventures. Later, companies can hire staff possessing important skills to Big Data. Studies and decisions should focus on the possibilities that lie within the use of Big Data to materialize upcoming developments in different fields.

Countless benefits in this regard can be found in business using Big Data, mainly added effectiveness in operations, improved course of strategies, offering better services to clients, developing new products and services, finding additional markets and consumers, etc. The vertical line refers to the proportion as to the number of ventures believing Big Data may be helpful in certain respects. According to fair calculations, the sector can generate $300 billion in yearly income for the healthcare sector in the United States, and €250 billion to European public administration. Another $600 billion possible yearly consumer surplus may be gained by means of private location data all over the world, with a 60% increase rate in profits. In the US alone, Big Data generates 140,000 to 190,000 critical skill-level jobs and 1.5 million data-savvy administrators. It goes without saying, then, that the sector is attractive and profit-making if ventured in the right way.

3.3.2 Challenges

Of course, benefits are always associated with drawbacks. Though Big Data can offer numerous advantages, countless obstacles appear as regards data capturing, saving, searching, distribution, analysis, and visualization. These, if remained unsolved, will turn the sector into a goldmine which cannot be accessed. In particular if the amount of information exceeds our processing abilities. For long, among these difficulties has been the issue of CPUs being heavy and I/O being poor – an imbalance that limits further Big Data explorations. CPUs every 18 months in terms of performance according to the Moore's Law, with disk drive doubling as well with the same speed. Still, disks' rotational speed has rather remained the same over time, causing I/O speeds to develop moderately while sequential I/O speeds develop sluggishly with density. Apart from these, the amount of information hikes exponentially at the same time, and yet our processing techniques remain somehow sluggish. In numerous vital Big Data applications, the ultimate methods are not able to best tackle actual issues, in particular with real-time analysis. Hence, to date we have not possessed the right tools to make use of this so-called gold mine properly.

Figure 3.1 illustrates the analysis process in common terms where knowledge is found while data mining. The difficulties appear mostly in data inconsistence and incompleteness, scalability, timeliness and data security. In advance of analysis, such data needs proper structuring; yet, given the countless forms of these sets, a sound way to represent, access, and analyze unstructured or semi-structured data is still a major problem. The question remains as to the way data can be processed in advance to better the quality prior to its analysis. Given the large size of these sets, often being gigabytes or more, as well as heterogeneous origins, present-day real-world databases are acutely prone to inconsistency, incompleteness, and noise in terms of content. Based on this, certain preprocessing methods – among them cleaning, integration, transformation and reduction – can be used to deal with noise and inconsistency. Numerous hurdles appear on the way of every sub-process once data-based applications take the fore. In what follows, we will discuss these hurdles within every sub-process.

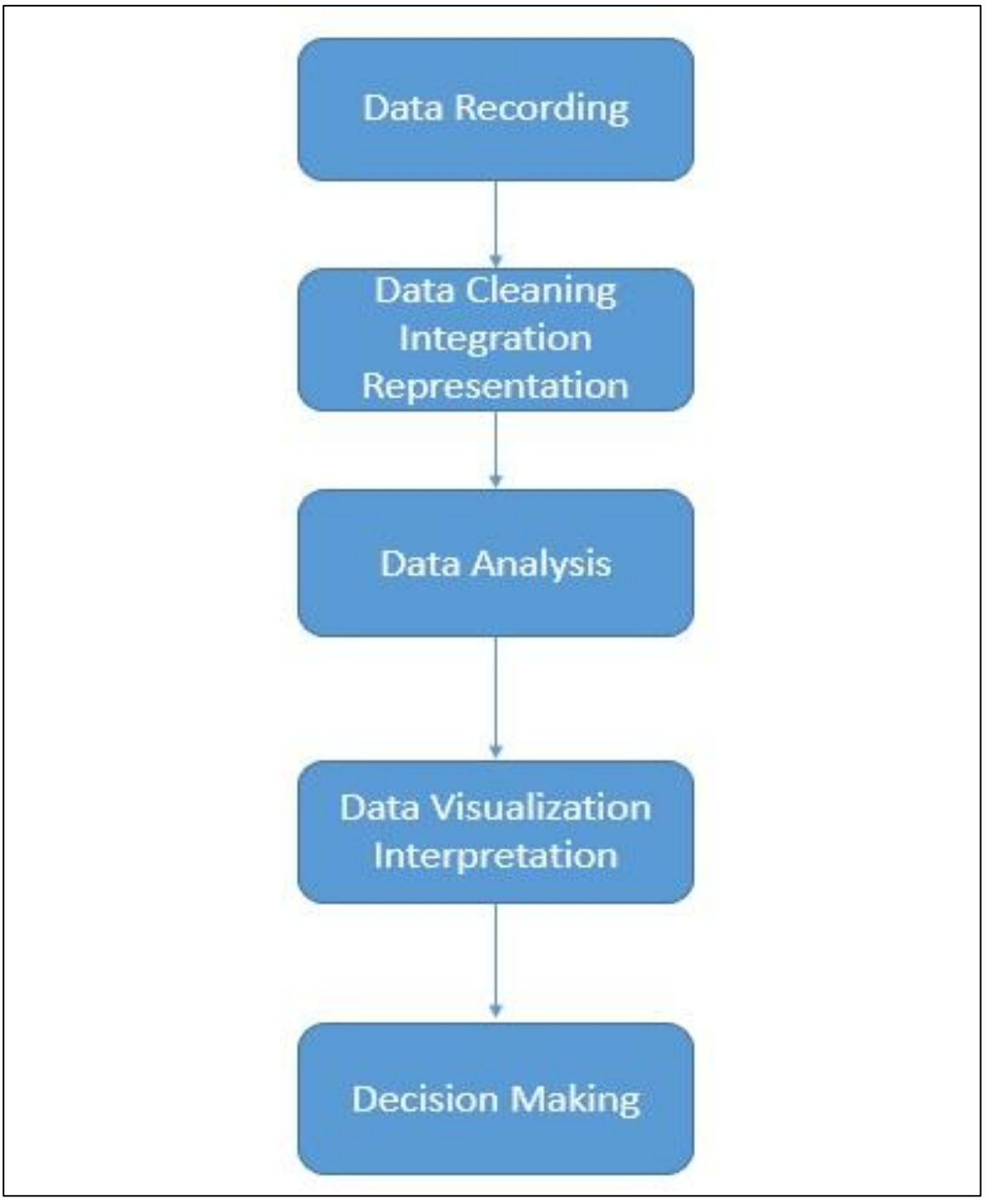

Figure 3.1: Steps of processing data

3.4 DATA CAPTURE AND STORAGE

Sets of data become larger as they are compiled via ubiquitous information-sensing mobile devices, aerial sensory methods, remote sensing, software logs, cameras, microphones, radio-frequency identification readers, wireless sensor networks, and numerous other sources. Some 2:5 quintillion bytes are formed each day with an exponential growth rate. Our ability to save has been becoming twice its previous size almost every three years as of the 1980s. In numerous disciplines, such as finance and medicine such data is often removed just because sufficient space is in short supply to save it all. Precious data like this is generated and gained expensively, only to be deleted in the end. Storage in mass quantities needs test data bases, large-scale storage for scientific measurements, and extensive output files to be re-examined in Big Data, all of which has altered our approach to obtaining and saving, these changes mainly appear in data storage devices, architecture, and methods of access. With added means of storage and increased I/O rates to solve the problems, it goes without saying that new inventions are long overdue. To begin with, Big Data to be accessed is number on in terms of priority in the discovery process. Accessibility has to be easy and quick to be further analyzed and wholly or in part tackle the shortage; in other words, being CPU-heavy and I/O-poor. Next, storage techniques that are not sufficiently developed, namely solid-state drive (SSD) and phase-change memory (PCM), can reduce these hurdles, but they will take a long time to do so.

Another major transformation is ahead: a major change in the conventional I/O subsystems .in older days, steady data used to be saved in hard disk drives (HDDs), which are known for far slower random I/O performance compared to sequential I/O performance. Also in the past, processing engines would format data and arrange query processing in a way to handle such shortcomings. Nevertheless, HDDs are quickly being taken over by SSDs now, with other techniques like PCM soon underway. Of course, all these new methods differ in terms of performance as regards sequential and random I/O operations at the same time - a process needing a review of ways to arrange storage subsystems for Big Data. Direct-attached storage (DAS), network-attached storage (NAS), and storage area network (SAN) in enterprise storage architectures are common, but they have major disadvantages in large-scale distributed systems. Aggressive concurrency and per-

server throughput are vital when using advanced scalable computing clusters, both of which the present day storage systems are devoid of.

Improving data access is one common approach to better data-heavy computing, and cover concepts such as data replication, migration, distribution, and access parallelism. In the section related to performance, the issues of reliability and scalability in data-access platforms were addressed. Platforms like CASTOR, dCache, GPFS and Scalla/Xrootd show extensive validation and performance measurement. At the same time, data storage and search schemes can result in high costs, whereas latency distributed data-centric storage has been a promising way for extensive wireless sensor networks (WSNs). In the work by Shen, Zhao and Li, a distributed spatial–temporal resemblance is shown in data storage schemes to offer enough spatial–temporal as well as resemblance data searching service in WSNs. The overall operations of those working within a group offers a way to materialize self-organization in such distributed systems.

3.4.1 Data Transmission

Commonly, Cloud data storage takes part in in shaping the related technology. As we are all aware, the network bandwidth capacity is the main issue in cloud as well as among distributed systems, in particular once communications are extensive and volumetric. Apart from this, cloud storage can cause security concerns in terms of ensuring integrity. There are numerous schemes suggested within a variety of systems and security approaches.

3.4.2 Data Curation

Data curation addresses discovery and retrieval, quality, adding value, reapplication and preservation in the course of time. In particular, this circles around certain sub-fields like authentication, archiving, management, preservation, retrieval, and representation. Present-day management instruments cannot handle Big Data given its growth and complexity – an issue that is likely to remain as there are important gains for scientists when investigating business patterns, fighting illnesses, and dealing with crime.

Despite added dimensions in the size of Big Data, today we can only work with it in limited amounts and fractions of petabytes, Exabyte’s and zettabytes. Conventionally speaking, one can

administer structured data in two ways: one with schema to store datasets, and one to use relational databases to retrieve. To handle extensive sets of data structurally, storage facilities and marts are common. A warehouse or storage comprises a setting to save, analyze, and report data back to users. Marts, on the other hand, circle around these storage facilities to make access and analysis easier. Warehouses chiefly save what is sourced by operational systems. It is important to preprocess prior to storage; these are cleaning, transformation and cataloguing tasks. Once completed, data can be used for advanced mining tasks online. Warehouses and marts are Standard Query Language (SQL)-based settings. Whereas NoSQL systems - that is 'Not Only SQL' – are presently applied to extensive and scattered management and design systems. The term may also imply ''not SQL'', which is not the case as NoSQL does not avoid SQL. Despite certain NoSQL systems being completely non-relational, a series of others just prevent selected relational functionality, for example fixed table schemas and join operations. Common-place Big Data platforms use NoSQL when cracking and moving beyond the strictness of normalized RDBMS schemas, but other Big Data platforms such as SQL stream and Cloudera Impala continue to employ SQL in database systems since it is secure and easy as query language, and also offers better performance as in Big Data real-time analytics. To save and administer unstructured or non-relational data, NoSQL uses a series of particular methods. For starters, saving and administering become two separate tasks, which is contrast to relational databases as they strive to do both at the same time. Such as approach is advantageous for NoSQL systems. Within storage – commonly referred to as key-value storage - NoSQL is concerned with scalability and high-performance.

Within management and administration, it supplies limited access, by which means related jobs are done within the application layer instead of spreading the logic all over SQL or DB-related languages. In this way, NoSQL systems become adaptable for modeling and simple for updating specific developments and applications. A majority of NoSQL databases possess a particular feature, and that is being entirely devoid of any schema with the most essential benefit being speedy modification of data structure and no need for table re-writes. On top of this, more adaptability is at hand once structured data is saved in a non-homogenized way. Within the data management layer, data is integrated and validated. Among NoSQL databases, Apache Cassandra is one of the popular ones as Facebook proprietary database for a certain period and introduced to public back

in 2008. Other NoSQL applications are SimpleDB, Google Bitable, Apache Hadoop, MapReduce, MemcacheDB, and Voldemort. Some firms using NoSQL are Twitter, LinkedIn and NetFlix.

3.4.3 Data Analysis

Big Data at first sight is sizeable, hence the most specific hurdle becomes scalability during analysis. Over the past twenty years, studies have focused on speeding up algorithms to tackle large sums of data and processing as per the Moore's Law. With these priorities, sampling, on-line, and multiresolution analysis methods become evident tasks. As regards Big Data analyses, increment algorithms show promising scalability, but not in all cases of machine learning. Certain studies focus solely on this subject and with data adding faster than CPU developments, a major change is indispensable in the field of [8] processor technology. Despite the clock cycle frequency doubling based on the Moore's Law, clock speeds remain far back. As an option, processors get equipped with added cores – a change that gives rise to parallel computing.

In case of real-time uses, such as navigation, social networks, finance, biomedicine, astronomy, smart transport systems, and internet of thing, timeliness is supreme, which topics begs the question how one may ensure such timeliness once the data is large in size. The issue is a striking one for stream processing in Big Data. Naturally, one may state that Big Data has caused not just new difficulties, but alternative ways to create both hardware and software systems. Here is where we move toward cloud computing to deal with numerous and separate jobs to be turned into larger sets of processors. While doing this, distributed computing is also taking a quick shape. In the upcoming section, we will look into this topic. Data security is now a bigger topic covering security protection, intellectual property, personal privacy, business confidentiality and financial information protection. Developed and developing nations mostly have related laws in place with an eye on increasing such security. Interested parties have to thoroughly address the laws as to where to save and handle data to ensure legal conformity. In terms of Big Data use, security challenges are even more striking given the causes: first, the size is simply monumental, thus varying the ways to protect; next, more security workload takes the priority, or else most Big Data saved in different locations can be subject to network threats, and hence increase the challenges.

3.4.5 Data Visualization

Visualization introduces knowledge more intuitively and efficiently through the application of graphs to convey information by offering knowledge located in large complicated sets of data. As a result, aesthetics functionality become prominent factors. The information retrieved in from certain schemes such as attributes or variables for information units, is important when analyzing data. Such an approach is much more intuitive compared to other advanced methods. For example, eBay enjoys hundreds of millions as active users and countless items are sold by its services each month, thus producing large sums of data. To make sense of it all, the company focused on a Big Data visualization tool known as Tableau. This is able to transform large, complex sets of data into intuitive images, thereby creating interactivity at the same time. As a result, those working for the company are able to visualize both search relevance and quality in order to follow most recent client feedbacks and carry out sentiment analyses.

As to the uses of Big Data, data visualization is specifically hard due to the size as well as the dimensions. Added to this, the most recent attempts to improve these tools have yielded disappointing performances in terms of functionality, scalability and response time. Therefore, what is needed at this stage is to change our approach when visualizing Big Data. To illustrate, the history mechanisms intended for visualization are data-heavy and deserve more effective methods. Uncertainty causes major hurdles to appear on the way to efficient visualization and can appear anywhere within the visual analytics. Updated framework to model uncertainty and assigning specifications to the development of related information are both much needed measures. Lack of skills plays a negative part in obtaining Big Data value.

In the United States, Big Data is likely to turn into a definitive factor in competition throughout various industries. In the same way, it calls for thorough critical thinking skills which goes beyond the available manpower based on present-day patterns, leaving a gap of 140,000 to 190,000 vacancies. Added to this fact is the type of resources getting harder to train as many years are needed to develop Big Data analysts with advanced mathematical skills and technical know-how. The same case is thought to be present elsewhere in the world, be it developed or developing. Estimates show yet another contested race form experts in Big Data.

Having examined certain hurdles associated with Big Data, one can state that there is enough confidence in proper skills to win over all these hurdles along the way because new methods are being developed each day. Numerous critiques and negative ideas are presented from skeptics, who claim that Big Data causes an end to theory, and wonder if the technology can assist us in really making better decisions. At any rate, most opinions are positive, thus leading to a series of developments in this field.

3.5 BIG DATA TOOLS TECHNIQUES AND TECHNOLOGIES

To gain further value from Big Data, new ways are to be created for analyses. Up to the present, numerous methods have been proposed to capture, curate, analyze and visualize Big Data. Yet, this is far from satisfying all requirements as they cover many fields as computer science, economics, mathematics, statistics, etc. Multidisciplinary methods are, hence, required for detecting precious information. The present methods will be dealt with later to make use of data-heavy applications. For now, we require proper platforms to give meaning to Big Data. Available platforms are based on three categories: batch processing, stream processing, and interactive analysis. In the first case, the platforms are in accordance to Apache Hadoop, namely Mahout and Dryad, which is more often for real-time analytics of stream data applications. Storm and S4 prove to be sound examples in case of large-size streaming platforms. Interactive analyses process the data in such settings and let users take over their own data analysis. Users are joined straightly to the computer, thereby increasing interaction in real time. Such data is subject to review, comparison and later analysis whether in table or graph form (or both) simultaneously. For example, Google's Dermal and Apache Drill are Big Data platforms arranged in accordance to interactive analysis. At this stage, other tools and platform will be introduced for each class.

3.6 BIG DATA TECHNIQUES

Special methods are required to properly run huge amounts of data with minimum run time. Naturally, such methods follow certain applications. Wal-Mart, to provide an example, uses machine-learning and statistical methods to investigate patterns present in vast amounts of transaction data. These patterns may lead to better position in competition as to pricing and

commercial advertisement methods. Taboo (Chinese enterprise similar to eBay) applies extensive data mining methods in the users' searched data as saved on its website, and applies a great amount of precious data to make decisions accordingly.

Big Data approaches cover certain fields as statistics, data mining, machine learning, neural networks, social network analysis, signal processing, pattern recognition, optimization techniques and ways for visualization. Special methods appear in all these fields which may go parallel on any given hour. Different optimization approaches are used to deal with quantitative issues in many areas like physics, biology, engineering, and economics. Numerous computational methods are available to solve global optimization matters, like simulated annealing, adaptive simulated annealing, quantum annealing, not to mention genetic algorithm normally based on parallelism with extreme efficiency gained in the end.

In this regard, stochastic optimization covering genetic programming, evolutionary programming, and particle swarm optimization are among other helpful and particular methods based on the nature itself. Yet, there is a high degree of complication in the use of memory and time. Countless studies have attempted to increase extensive optimization via cooperative co-evolutionary algorithms. Real-time optimization is as well needed in a large number of Big Data uses like WSNs and ITSs. Data reduction and parallelization, separately, offer other options in such problems. Statistics deal with gathering, arranging, and making sense of data, with related methods applied to use correlation ships and causal relationships among various aims. Statistics, in addition, offer numerical description, but standard statistical methods do not often appear suitable for managing Big Data, and numerous studies point to the adoption of conventional approaches or entirely new ones. Some suggest efficient approximate algorithms for large-scale multivariate monotonic regression as a means to measure monotonic operations related to input variables. A different method to analyze statistics according to data circles around scale and parallel applications of such algorithms. In this regard, Statistical computing and learning have become major topics of interest lately, with data mining dealing with obtaining vital information or trends from data, like clustering analysis, classification, regression and association rule learning. This, of course, calls for techniques related to machine learning and statistics as well.

In comparison, the mining of Big Data mining can be more a more intensive task. Clustering, for instance, is natural to Big Data as it expands present techniques like hierarchical clustering, K-Mean, and Fuzzy CMean to the extent that they can handle large amounts of work. In many cases, these improvements analyze a fixed portion of Big Data, and can be different in terms of using the outcomes to come to distinctions for the whole data. Such clustering uses CLARA (Clustering Large Applications) algorithm, CLARANS (Clustering Large Applications based upon Randomized Search), BIRCH (Balanced Iterative Reducing using Cluster Hierarchies) algorithm, and similar types. In addition, genetic algorithms cluster the criteria for optimization as a mark of quality. Big Data clusters have gone beyond what they are and become wide-spread and parallel. Discriminant analysis, for instance, incorporates efficient algorithms into the operations with focus on minimizing computational complexity. Bioinformatics is a good example of such shift to increased data-based operations, eventually shifting the paradigm from common single-gene biology to a combination of integrative database analysis and data mining. Such an updated approach facilitates the analysis of extensive sets of genetic activities.

A hot subject in AI is machine learning and includes algorithms enabling computers to change patterns of behavior as per the empirical data. A common feature in this approach is seeking knowledge and automatically coming up with smart decisions. As far as Big Data matters, one has to upgrade such algorithms first in the form of supervised and unsupervised learning. Deep machine learning is, in this line, yet another topic in AI along with countless others, including Map/Reduce, Dryad LINQ, and IBM parallel machine learning toolbox making it possible to extend machine learning even further. To illustrate, Support Vector Machines (SVM) as basic algorithms that divide and regress problems have drawbacks in terms of scalability of memory and computation time. Lately, of course, Parallel SVMs (PSVM) have come to the fore to tackle this problem. Numerous scale machine learning algorithms can be found and, yet many scaling issues at the same time are confronted in sub-categories like large-scale recommender systems, natural language processing, association rule learning, and ensemble learning.

A tried and tested method, artificial neural networks (ANN), are used in numerous fields with promising results for tasks like pattern recognition, image analysis, adaptive control, etc. Large

portion of present-day ANNs in AI focus on statistical measurements, classification optimization and control theory. Commonly known is the fact as the hidden layers and nodes increase in a network, their accuracy also increases. Still, ANN complexity can extend the learning time, whose process in Big Data will evidently become even more time- and memory-intensive. Neural processing of vast amounts of data generate extended networks, bringing us face-to-face with two major issues: first, common-place training algorithms are not effective, and second, training time and memory restrictions become severely hard to follow. As a matter of course, there are two ways to deal with this issue: minimizing data size by means of sampling and maintaining the neural network; or extending the networks as such. As an example, mixing deep learning and parallel training implementation offers two solutions when handling Big Data. Different ways to visualize can help form tables, images, diagrams and other intuitive solutions to make sense of data. Though the task may be challenging compared to smaller sets, as there is the issue of 3Vs or 4Vs complexity. To expand common ways to visualize is already in use, yet with long way ahead of itself.

Speaking of extensive visualization, most studies apply feature extraction and geometric modeling methods to minimize greatly the data size prior to rendering. In order to interpret data better and more intuitively, some even attempt to run batch-mode software rendering with maximum resolution in a parallel fashion. Crucial to the process is the selection of appropriate data representation for Big Data visualization, data is compacted to offer better approximation to mass data. Social Network Analysis (SNA) developed as a crucial method in present-day sociology takes social relationships within the context of network theory with nodes and ties, thereby finding applications in anthropology, biology, communication studies, economics, geography, history, information science, organizational studies, social psychology, development studies, and sociolinguistics. At hand as a consumer tool. SNA also covers social system design human behavior modeling, social network visualization, social networks evolution analysis, graph query, and mining.

These days, online social networks and social media analysis are common practices. In this respect, SNA faces the problem of size in Big Data because reviewing a network with unlimited connected

objects is naturally expensive to compute. In relation to this, there are a couple of subjects, social computing and cloud computing, which assist SNA in some ways. Advanced Big Data techniques cover distributed file systems, distributed computational systems, massively parallel-processing (MPP) systems, data mining based on grid computing, cloud-based storage, computing resources, granular computing and biological computing. We will deal with these topics later. In the meantime, numerous authors consider dimensionality a major drawback in Big Data. As a matter of fact, Big Data is not favored to be limited in volumetric terms, but in terms of advanced features of the data available. In other words, handling high-dimensional data is regarded as a challenge by researchers. The advanced methods to deal with such data in an intuitive manner are subject to decreasing size. In a way, one attempts to map such data into a lower space with the least information to be lost down the line. Many approaches propose such ways to shrink size in linear mapping, namely principal component analysis (PCA) and factor analysis. On the other hand, non-linear methods are kernel PCA, manifold learning methods like Isomap, locally linear embedding (LLE), Hessian LLE, Laplacian Eigen maps, and LTSA. Nowadays, generative deep networks also known as auto encoder have proved effective in minimizing non-linear dimensionality. There is also another satisfactory approach known as random projection.

3.7 CHARACTERISTICS OF BIG DATA

3.7.1 Volume

The term “Big data” points to the amount of data in formation by numerous sources such as text, audio, video, social networking, research studies, medical data, space images, crime reports, weather forecasting and natural disasters, etc. Based on , such data may simply be the conversations on social networks, web server logs, traffic data, satellite pictures, I-casts, banking transactions, MP3s, web pages, government scans, GPS data, telemetry from automobiles, market information, and the list goes on. Yet, all this data – as unstructured as it is – may not be dealt with using conventional methods like SQL. To illustrate, one cannot use the query “select something from some table where something equals something”. We know that disorganized data is far from normal tabling datasets commonly in use such as RDMS systems, Oracle and SQL Server. By the same token, one has to understand that this peat-byte size data, rendering SQL useless as a result.

3.7.2 Velocity

Speed is vital for bulky and complicated data a decisive. Suppose the velocity in which such data as on mobiles and the Internet is being created. It is far from manageable and straightly related to sizeable amounts as referred to in Section. Given this fast flow of data, proper tools are necessary for enterprises to handle data as deemed fit. In this respect, a line from an IBM advertisement form reads: "you wouldn't cross the road if all you had was a five-minute old snapshot of traffic location. There are times when you simply won't be able to wait for a report to run or a Hadoop job to complete." This statement implies the necessity for a feedback loop to transfer data from input into the decision. As a result, not just speed, but moving such data is vital for extensive storage and subsequent handling and synthesis. In line with this issue, there are two causes for due processing: (1) saving the input because it comes in with high velocity, thus needing careful analysis upon occurrence on the fly; and (2) responding to data since applications call for it.

3.7.3 Variety

Data takes different forms: audio, video, text, images, or else, thus increasingly the challenge. This is the reason one may not refer to it as a relational database as the hard job entails setting up a mechanism in a way to incorporate data properly. There are countless software and browsers used on the Internet to dispatch data to the cloud. It has to be remembered that a majority of this data originates from actual human interface, thus subjecting it to mistakes. Variety in terms of data is seen as impacting integrity in a direct way. Simply put, more variety causes more errors.

3.7.4 Veracity

Veracity implies correctness, that is, how confident data can be, or whether it is what states to be. Meaning, therefore, is gained based on the results of data considering any space being worked upon. Prior to veracity in Big Data, researchers and specialists thought the arriving data is safe and sound – a belief almost in line with conventional ideas about data storage. Today, looking back we see disorganized data possibly originating from Facebook posts, tweets, LinkedIn posts, and others. We rely on all there is to see. Despite the fun when read and contributed, these posts cannot be trusted in terms of commercial and critical aspects, to give an example. Veracity is paramount in data management and subsequent analysis and end results. Let us not forget that normalization is

used toward relational and conventional datasets ensure accuracy – data that is reliable and there are no copies of it. Hence, it is essential to clean up big data using certain applications and algorithms. Apart from this, a description is needed as for reliability as per the source and application of data in any way that is may be.

3.7.5 Validity

This may look like veracity at first sight; though they are separate issues as validity is about correctness and accuracy concerning the desired application. Put differently, data can be veracious but invalid unless comprehended thoroughly. In critical terms, a dataset can be valid in case of certain uses, but not so for others. Albeit handling data with unclear ties observed in the beginning, the verification ties have to be figured somehow among the components, so as to validate for the desired application as much as it can be. Take the illustration in. where a doctor may just retrieve information from clinical trial as to the symptoms and not reaffirm such information – an unthinkable task. One more example as in shows us we can confirm the possibility of storm in a certain place as per the satellite information to match Tweets related to the effect on the people living there.

3.7.6 Volatility

When it comes to this topic, one may refer to retention approaches in organizing big data as applied on a daily basis at work. With this duration over, one can easily delete it. Another sample can be given from businesses online that are unwilling to store sales data for one year. Since the guarantee for default is overdue after this period, the information may not ever be retrieved. Big data is subject to the same principle in actual settings of storage – a topic highly intensified in case of big data and as opposed to conventional systems. Here, the storage duration and pass, leading to costs incurred for security and further retention. In a way, the importance of volatility owes itself to volume, variety and velocity all at the same time.

3.7.7 Value

This V in the characteristics of big data is particular in the sense that value is an ideal result when handling data and there is an ever-persistent intent to add to the value of datasets to be handled. At this stage, one has to seek actual values; that is, value has to go beyond expenditure related to

ownership and administration. Vital is to invest in saving data which can be done economically once bought. Though lack of investment in sufficient storage will damage precious data. An example is saving clinical trial information related to new medication in insecure and unreliable spaces which can cut down on expenses now, but endanger the content later.

In addition, value highly relies on the way of administration, too – in other words, the way policies and structures are drafted so as to generate homogeneity between reward and risk in data. In the meantime such drafts, unless created and applied properly, can limit enterprises' ability to fully determine data value. That is to say, data becomes less worthy. In addition, actual value relies on the client purchasing the data. Also, it should not be forgotten certain data may not be valuable once gathered and in accordance to risk factors, but it may gain value in the course of time. As illustrated in, one can see the results of one to five years for data in percentage of hardware, non-hardware, and overall costs. As economies slow, less money is dedicated to IT, making storage more costly than ever before with almost %47 of IT budget spend on infrastructure maintenance, another %40 to handle information and %13 for future investments. Data may travel among different tiers. Upper tiers add to value, put differently, the data located there is less likely to be subjected to risk. Henceforth, certain ventures may undertake such steep prices for saving data only to ensure safety and security, thereby adding to value.

3.8 INTRODUCING HADOOP

Hadoop appeared in the Google study of MapReduce in 2004, and later began to expand in 2005. Then, it was intended as an open-source backup of a search engine known as Nutch. Later, Hadoop was set apart from Nutch to become a different initiative as per the Apache Foundation. Currently, it is the most famous of MapReduce products with numerous ventures being supported, advised and trained with its programs. Internally, Hadoop is based on Java, but given its quick application, the non–Java users also had to be covered. Hadoop morphed with certain additions and sub-initiatives to do the above task and find its way into business; these are:

3.8.1 Hadoop Streaming

Hadoop have one of the most important utilities it is for distribution data for both static and dynamic. for the last one, Hadoop has ability to processing, not just static data but also stream data, it happens in MapReduce program Which allows MapReduce use with any command-line scripts, thus making it applicable with UNIX and Python programmers and also for ad hoc tasks.

3.8.2 Hadoop Hive

Those applying MapReduce learned that making such programs is highly tense and subject to errors difficulty in testing. Better expressive languages were needed like SQL to concentrate on problems and not insignificant uses of ordinary SQL artifacts, such as the WHERE clause, GROUP BY clause, JOIN clause, and others. Apache Hive was improved to offer data warehouse (DW) benefits in case of mass data. Appliers could write queries in this language bearing resemblance to SQL. The Hive engine changes them to low-level MapReduce tasks, with expert appliers able to form user-defined functions (UDFs) in Java. Hive backs standard drivers like ODBC and JDBC, and is ideal tool for making Business Intelligence (BI) kinds of applications for data saved in Hadoop.

3.8.3 Hadoop Pig

Despite the drive behind Pig being the same as Hive, the latter uses a language close to SQL – that is, declarative. In the opposite way, Pig is procedural and functions best in cases of data pipeline, thus popular among experts in fields like SAS. Pig is also best for extracting, loading, and transforming – or ELT activities.

3.8.4 Hadoop HBase

The previous projects are all batch works. There have been calls for real–time data lookup in Hadoop, which lacked a native key or value store. Take a Social Media site for example Facebook. To see someone's profile, a quick response is anticipated and not after numerous batch runs. Examples like this inspired the HBase platform to emerge.

This is, of course, the tip of the iceberg so to speak of Hadoop and its branches. The illustrations given before offer enough insight as to the way it morphed and why, mainly as initiation from MapReduce to deal with large amounts of text data, later to change to a common model to back up common venture applications like DW, BI, ELT, as well as real-time lookup cache. In spite of

MapReduce being helpful, the change to common Enterprise applications in fact gave it more ground to enter the general flow of computer business.

Another point is that firms are in a struggle to process extensive amounts of data. Hadoop for long stayed a system by which users arranged jobs running on whole clusters. These jobs were to be managed as First In, First Out or FIFO, thus causing extended runs and insignificant jobs occupying using up resources that should have been allocated to more vital though smaller ones. In order to handle this, more complex job schedulers were developed in Hadoop like Fair Scheduler and Capacity Scheduler, though Hadoop 1.x as previous to version 0.23 continued to experience issues with scalability caused by severely flawed moves in designing. At Yahoo, experts, noticed this problem as the nodes (http://developer.yahoo.com/blogs/hadoop/scaling-hadoop-4000-nodes-yahoo-410.html) regenerated in their thousands. With improved understanding came a return to design and re-evaluate certain basic notions within the first Hadoop, thus leading to large-scale overhaul of its core platform. Hadoop 2.x driven from version 0.23 was released as the outcome. (This book will cover version 2.x with appropriate references to 1.x, so you can appreciate the motivation for the changes in 2.x extra sentence.

3.9 BENEFITS TO USE HADOOP

1. It is a free software, thus economical.
2. MapReduce establishes its framework in programming.
3. It back up present-day database and analytics foundations.
4. Big data is a major chance for solution providers. For instance, $740 million dollars have been put by Intel as investment for Hadoop's increased use
5. Fast-processing of big data is possible via distributed models since the higher the number of nodes, the higher the processing power.
6. Malfunctions within hardware have no impact on data and its applications.

3.10 HADOOP COMPONENT

Hadoop hovers around distributed computing with an HDFS file system known as Hadoop Distributed File System. It is not prone to error and may be used with minimum expenditure. Hadoop is ideal in case of big data thanks to improved access speed in use. Being based on clusters, it has nodes of data and name as separate. Under the best settings, it can be improved in terms of performance by means of appropriate task setting within the scheduler. In Hadoop, map-reduce gathers data as per query. A lots of data exists, hence the term coined as Big Data. The question is why we need this term. As stated before, data lies around without our knowing how to harvest it. The simple reason for this inability is lack of tools for analysis. For example, a group of experts attempt to analyze what they have as dataset. Someone from an enterprise claims to be able to do this job, and eventually takes 15 years to do so – after which period the data is rendered useless due to time lapse.

In the era when we cannot wait for five seconds to open a Google page, it is of course difficult to imagine such extended periods needed for analyses. Speaking of Big Data makes "HADOOP" to pop into mind first as it is a famous product in the market and, being based on Linux, it is also applied by major firms as Google, Yahoo, and others. The name node is a type of master node with information. We can also use the term ‘meta data’ when speaking of all data nodes, free space, all data stored, active and passive data nodes, task trackers, job trackers and many other configurations like replication of data. A data node is a slave node in Hadoop and applied to store data; the task tracker follows tasks in progress within the node as well as those originating from the name node.

The Hadoop architecture is based on HDFS, short for Hadoop distributed file system. Here, the data is spread – ideally - evenly on each node. Once users retrieve, supply, change, or remove certain data, from Hadoop, the system gathers such data from each related node and perform the rest as we require.

Scheduler in Hadoop: this has an important part in managing big data. A fair scheduler as the term implies arranges tasks so that the resources are divided in equal terms among users with no extra load inserted anywhere. The scheduler handles all resources dedicated to the nodes and assists in

keeping constant the load on all of them. Scheduling helps in big data processing in the following way: imagine ten data nodes within a Hadoop cluster and an unfair scheduler unable to run the resources effectively. The solution is to assign 5 data nodes out of 10 with an x amount of time to do the job. In case of a fair scheduler as to assigning work in the cluster, around x/2 the amount of time will be required to accomplish the entire function.

3.11 HADOOP ARCHITECTURE

A small Hadoop cluster has one master and numerous working nodes; the former involves a job tracker, task tracker, name node and data node. The job tracker monitors execution and harmonizes all other tasks through scheduling based on the system at work in the job tracker, which also keeps in place all the processing resources within the Hadoop cluster and assigns them to the task tracker to be carried out in accordance to application request. This job tracker can get updates from the task tracker to monitor all the process of execution, and also harmonize all activities to deal with malfunctions if needed. The job tracker needs to operate on the master node given its duties - as stated before – regarding all MapReduce jobs within the cluster.

3.11.1 Task Tracker

This feature tracks the sequence of the job tracker and maintain regular updates by running tasks and preparing reports for the job tracker. In turn, the job tracker maintains these records for each job. All task trackers are equipped with a series of slots which highlight the number of tasks to be admitted.

3.11.2 Name Node

In the HDFS, name nodes play a major role as following the clusters with a directory tree related to all files present in the system. The data within these files is not saved by the name node, and the operations work with this node anytime a file is to be found or once additions, movements, or deletions are due. Then, the node reacts to valid requests and provides a series of related data node servers where the specific data is kept. This is a single drawback in HDFS clusters, thereby render as a low-availability system since access is limited and the system ceases to operate once the name node is in active.

3.11.3 Data Node

In HDFS, this node - otherwise regarded as slave – stores data. As data nodes are many, they can save copies of data in three different places. Data nodes and name nodes co-operate, with the former notifying the latter as to the blocks it undertakes once the system is started. Here, no clusters or data access are influenced once data nodes stop operating. In essence, data is saved in the data node, which in turn is arranged with huge sums of space on the hard disk.

3.11.4 Hadoop Distributed File System (HDFS)

As a distributed network to save such files on the related nodes. This system follows a master/slave design and cluster with just one name node, a master server running the file system name-space and monitoring access from users. The data is grouped as either 64 MB or 128 MB blocks with three duplicates for each in separate spots knowns as data nodes. The name node carries out the jobs related to file system name-space, including opening, closing, and name changes and directories; in the meantime, the data node saves read and write requests coming from the user and decides on the block mapping. Data nodes undertake other tasks such as making, removing, and copying any block as per requested by the name node. In this system, the throughput access is maximum, thus making it ideal for use in big data. Apart from this, HDFS enjoys advanced resistance to errors and may be applied with any economical hardware equipment.

3.12 APACHE HADOOP

The basic inspiration behind YARN has been to separate the two main duties of the Job-Tracker, mainly running the resources and controlling the job schedules, to form a worldwide ResourceManager and a per-application ApplicationMaster (AM). The ResourceManager and per-node slave, the NodeManager (NM), combine to create an updated and original mechanism to run the operations in a distributed style. The ResourceManager serves as the top decision-maker deciding resource allocation throughout the entire operations within one system. On the other hand, the per-application ApplicationMaster practically serves as a framework unit responsible for resource bargaining from the ResourceManager and operating alongside the NodeManager(s) so as to carry out and control related jobs. The ResourceManager is equipped with a connectible scheduling element in charge of assigning resources to different applications in accordance to the

all-too-well-known factors like capacity, queues, and others. By design, the scheduler is pure as it carries out no controlling or follow-up jobs related to different uses, which means that there is no assurance certain applications may be re-initiated should there be any malfunction within the system. The scheduler simply does its jobs as per the resource needs within an application through the use of abstract notion in containers, those holding different aspects like memory, CPU, disk, and network data. As stated previously, the NodeManager is the per-machine slave in charge of initiating application containers, controlling use of resources as CPU and others, and eventually providing updates of the events to the ResourceManager. In turn, the per-application ApplicationMaster takes on bargaining for sufficient resource containers from the Scheduler, following up their related conditions, and supervising the process. . Seen from a system viewpoint, the Application Master operators like an ordinary container. See Figure 2 to catch a glimpse of the related design.

A noteworthy application of MapReduce in recent YARN systems is the ability to re-utilize present MapReduce formats with no need for major reconfigurations – a feature that plays a key role to maintain compatibility in the available uses of MapReduceons with the users themselves.

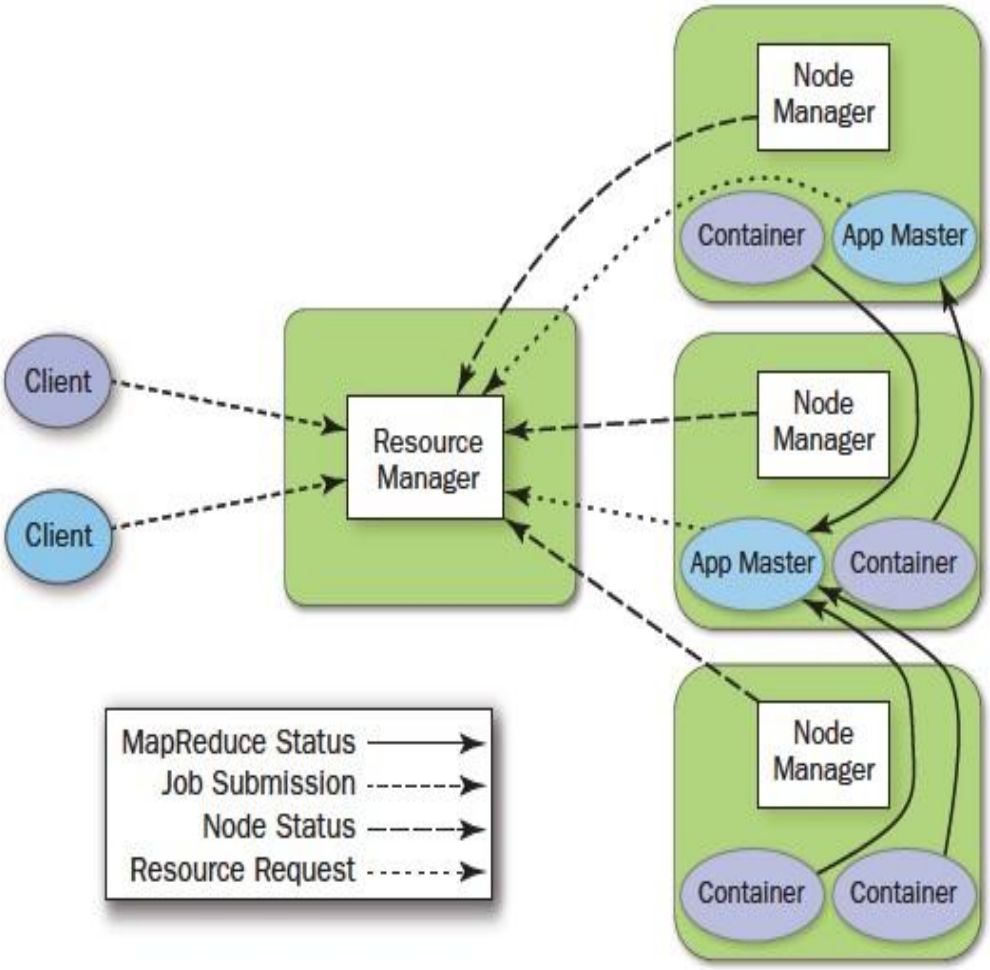

Figure 3.2: YARN control

3.12.1 YARN Components

Given its additional capabilities, YARN offers other elements to the Apache Hadoop operations for improved monitoring by end-users and also better-developed features for the entire Hadoop environment.

3.12.2 Resource Manager

As stated previously, the YARN ResourceManager chiefly serves as a pure schedule, thus severely bound by arbitrating demands of applications for accessible resources. Here, clusters are used at

most by maintaining the resources being applied in case of limitations like capacity guarantees, fairness, and service-level agreements or SLOAs. In order to make room for such policy constraints, the ResourceManager is equipped with a pluggable scheduler for the use of certain algorithms related to capacity and fairness if deemed required.

3.12.3 Application Master

YARN contains a specific feature known as ApplicationMaster as an example of a library based on framework and in charge of resource allocation from the ResourceManager and operating alongside the NodeManager(s) to carry out and control the containers and the amount of resources being used. Another one of its duties is to bargain for the right resource containers from the ResourceManager, following up related conditions, and controlling task progression.

With its specific design, the ApplicationMaster helps YARN with these updated qualities:

1. Scale: it offers most of job-related operations undertaken by JobTracker I na way that all the system may be scaled more intensively. According to experiments, such jobs can scale without difficulty up to 10,000 node clusters with new equipment. Being pure, this scheduler needs not supply fault tolerance for resources within any cluster. Instead, through moving tolerance to the ApplicationMaster, locality replaced being global in terms of monitoring. In addition, as an ApplicationMaster is made for each use, it hardly becomes congested inside the cluster.
2. Openness: System generalization is achieved by transferring the entire code for framework inside the Application-Master to back up numerous frameworks such as MapReduce, MPI, and Graph Processing.

The above qualities are achieved as per important decisions in designing YARN, namely:

1. Transfer as much complexity to the ApplicationMaster and offer enough functionality for adequate adaptability and power for those writing the frameworks;
2. Do not rely on the ApplicationMaster(s) as they are user nodes and, in some ways, very specific services; and
3. The YARN system (ResourceManager and NodeManager) needs maximum self-protection against erroneous or flawed ApplicationMaster(s) and resources provided.

In actual settings, all applications possess specific cases of ApplicationMaster, though one may easily use an ApplicationMaster to run numerous applications in Pig or Hive to manage a series of MapReduce. Apart from this, the feature goes as far as extended services, those managing their own applications, possible through initiating HBase in YARN with a tailor-made HBaseAppMaster

3.13 RESOURCE MODEL

YARN offers an inclusive resource pattern with applications through ApplicationMaster having the ability to seek out resources for very detailed requirements like:

1. Resource name to cover hostname, rack name, and perhaps complex network topologies;
2. Memory available;
3. The CPUs number/type of cores; and
4. Resources including disk/network I/O, GPUs, and others.

The ResourceManager in YARN mainly is focused on scheduling by assigning the resources at hand to the requesting applications and not the job of managing each-application state. The scheduler merely deals with a general resource profile for the applications and disregards local optimizations and internal flow. Indeed, YARN totally moves away statically delegating maps and slot reduction by taking a cluster as a resource pool. Thanks to such evident distinction and the modular feature as discussed earlier, the ResourceManager can meet major design needs as to scalability and provide other paradigms.

Unlike numerous other schedulers, the ResourceManager can symmetrically ask for added resources from an application in progress. Incidents like this are common once resources are in short supply and schedulers aim to recollect certain resources allotted to an application. In YARN, ResourceRequests may be rigid, in which case the ApplicationMasters can have major adapatability in temrs of meeting such allotment requests in the form of taking non-crucial containers for computation, checkpointing status, and moving the computation to other containers. In all, the scheduler makes room for preservation, unlike others annihilate containers due to limited resources. Should the application be non-collaborative, after a while the ResourceManager may

gain the necessary resources by ordering the NodeManagers to basically finish containers using force.

The malfunctions in the ResourceManager are major incidents and impact access to clusters. From this point onward, the ResourceManager can restart running ApplicationMasters while retrieving the previous status. In case restart is supported by the system as it is the case to commonly check for errors, the users' pipelines are automatically started. Unlike Hadoop 1.0 Job Tracker, one has to remember the tasks not undertaken by the ResourceManager. Except for following the flow of execution and fault tolerance, the ResourceManager refuses availability for application status or servlet which is now within ApplicationMaster, and does not undertake following formerly completed jobs – which is one currently given to the Job History Service as a daemon operating on a different. Such operations are in line with the notion that the ResourceManager can only deal with active resource scheduling to assist the major elements within YARN in better scaling as opposed Hadoop Job Tracker.

3.14 TAXONOMY FOR HADOOP SCHEDULING USED IN BIG DATA

The schedulers in Hadoop are meant to better apply resources and increase functionality not to mention better job production and advanced response time toward interactive tasks when resources are to be divided with fairness among all users. The related taxonomy appears in Figure 3.4. This scheduler can be categorized with the following factors: environment, order, energy, resource awareness (free slot and disk space), CPU time, I/O utilization, time, and action plan. The algorithms commonly aim to moderate execution time for parallel applications as well as deal with data-processing issues. Scheduling is mainly about reducing costs, use of resources, and time needed in order to maximize throughput via proper assignment of jobs. Here, the grouping relies on proper and satisfactory resource supply and accessibility, plan of action, and finally moment.

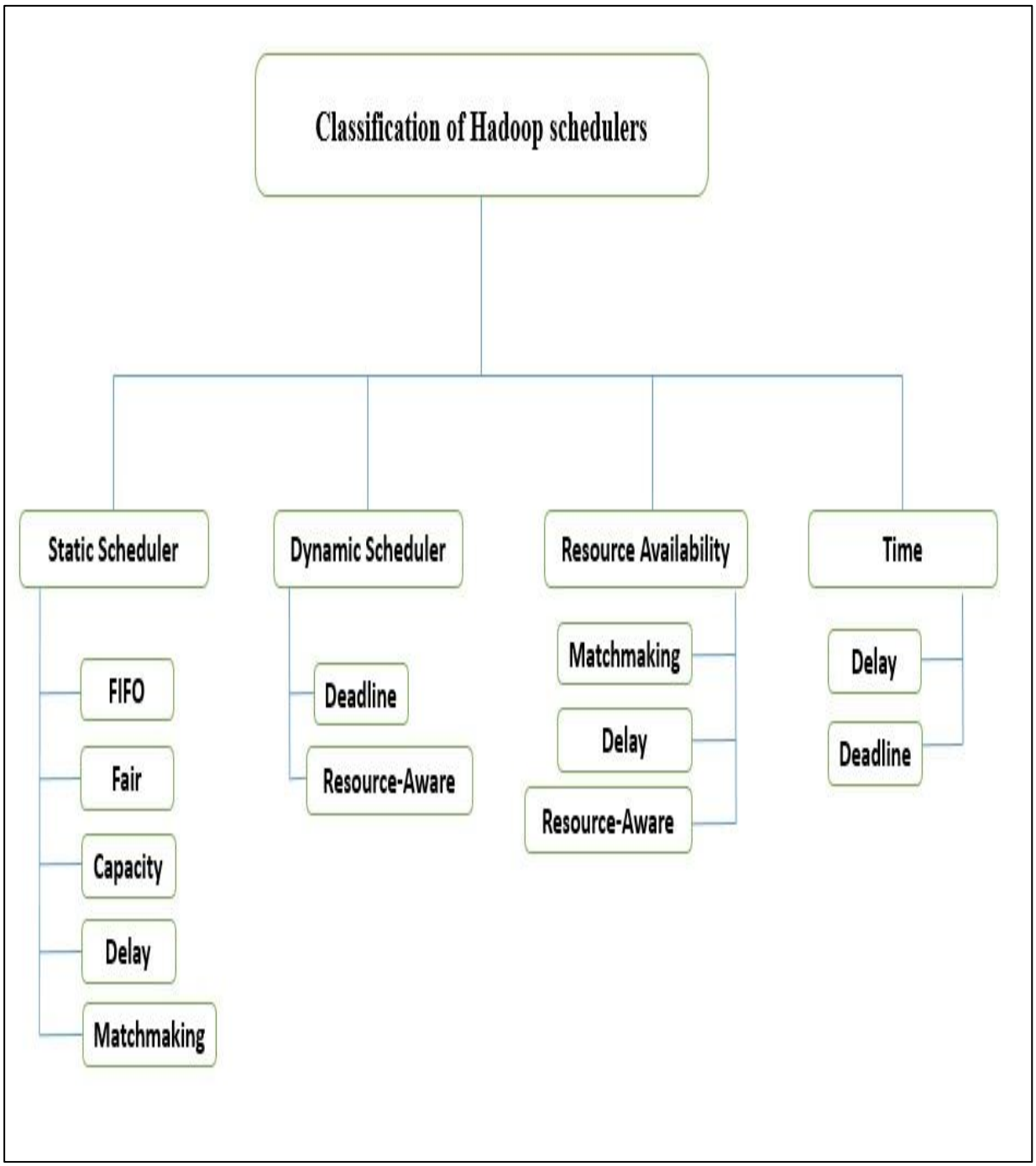

Figure 3.4: Hadoop Classification for scheduling algorithms

3.14.1 Static Scheduler Policy

In static scheduling policy to assign jobs in processors, one has to is attaining before the program to begin the job running time, in ending time. The resources needed for processing and job execution are considered only at the end. The static approach reduces the total operation time in the available programs.

3.14.2 Dynamic Scheduler Policy

In this approach, jobs are assigned throughout the execution time itself, and the scheduler is partly aware of the available resources in advance, but the environment for jobs to be done may be unfamiliar and jobs are carried out within their lifespan. While execution is in progress, decisions are made and dynamic environments are implemented to the operations.

3.14.3 Based on Available Resource Scheduler Policy

In essence, such a policy is centered round the resources necessary for any job and to conform performance to the use of resources, which may be in the form of I/O, disk storage, memory, or CPU time.

3.14.4 Time Based Scheduler Policy

In this approach, the job ends as per required by the user since a time limit exists to accomplish the job accordingly. The user determines the ending date, and next observes if the job is carried out in the stated period. Such a date may be requested by the user, who can check if due date is observed for completion.

3.15 BIG DATA TECHNIQUES AND THE KEY IDEA

- Despite the fact that we have implemented many assumptions in previous studies, the key is that we can process the data quickly. However, there are significant obstacles in the speed at which data taken from static storage can be viewed. There is a conflicting and interesting ability / formed to enumerate axons in them, and data transmission across the system is much slower. Part of the natural attributes of all Big data Datum technologies are the utilities:
- Data is disseminated over a few hubs (System I / O speed << Nearby Circle I / O Speed).
- Applications are conveyed to data (hubs in the bunch) rather than a different way.

- However much as could be expected, data is prepared neighborhood to the hub (System I/O speed << Nearby Plate I/O Speed).
- Irregular plate I/O is supplanted by successive circle I/O (Exchange Rate << Plate Look for Time).
- The motivation behind every single big data Datum ideal models is to align input/yield (I/O) to accomplish execution enhancements .

3.16 THE PATTERN OF DATA DISTRIBUTION ACROSS MANY NODES

Big data is serious of complex data that can't be prepared to utilize the assets of a solitary machine. The utilization of ware machines can be seen as one of the sale purposes of big data. A common item machine would must a 2– 4 TB circle. Since Enormous data alludes to a huge datasets more than that, thus, data would be appropriated over a few hubs. Note that it isn't generally important to have many TB of data for being handled to disperse data over a few hubs. It is known that Enormous data frameworks generally processing data to be set up on the hub. Since countless are taking part in data handling, it is fundamental to appropriate data over these hubs. In this manner, even a 500 GB dataset would be disseminated over numerous hubs, regardless of whether a solitary machine in the group would be fit for putting away the data. The reason for this data circulation is twofold :

•Every datum square is reproduced crosswise over more than one hub. This does the framework versatile to disappointment. On the off chance that one hub fizzles, different hubs have a duplicate of the data facilitated on the fizzled hub .

•For alike preparing reasons, a few hubs participate in handling of the data. Hence, 50 GB of data shared inside 10 hubs empowers every one of the 10 hubs to process their own sub-dataset, accomplishing 5– multiple times improvement in execution The peruse may we inquire as to why every one of the data isn't on the system record framework (NFS), in which every hub can pursue its bit. The appropriate response is that perusing from a nearby plate is altogether quicker than perusing from the system. Big data frameworks make the nearby calculation conceivable in light of the fact that a vocation is begun only after the application archives are duplicated to every datum hub. This I will be explaining it in the following area .

3.17 APPLICATIONS ARE TRANSFERRED TO DATA

The three-level engineering was penetrated into us, because of installing the J2EE wave. In the three-level programming model, the prepared data in the unified application level subsequent to They are brought across the system. We were utilized to the thought of data being circulated however the application has been brought together. Enormous data can't deal with this system overhead. Move the terabyte data to the application level will immerse the systems and present extensive wasteful aspects, potentially prompting framework disappointment. In the vast world of data, data is transposed across the hubs, yet the application moves to the data. Note that this procedure isn't simple. The application does should not exclusively be moved to the data yet all the needy libraries additionally should be moved to the preparing hubs. On the off chance that your group has several hubs, it is anything but difficult to perceive any reason why this can be an upkeep/sending bad dream. Thus Enormous data frameworks are intended to enable us to convey the code halfway, and the basic big data framework moves the application to the preparing hubs preceding employment execution.

3.18 LOCAL DATA IS PROCESSED TO A NODE

This kind of data is being handled live to the hub is a characteristic result of the prior two traits of Enormous Data frameworks. All large Datum programming models are suitable and process-based. The system I / O is requests of size slower than plate I / O. Appropriated data to different hubs, therefore libraries of the applications have been moved to hubs, the main objective is to execution appropriate process to the data set up. In spite of the fact that handling data neighborhood to the hub is favored by a normal Big Data framework, it isn't constantly conceivable.

Enormous Data frameworks will plan assignments on hubs as near the data as could be expected under the circumstances. It can be found in the areas to pursue that for particular kinds of frameworks, certain errands require getting data crosswise over hubs. In any event, the outcomes from each hub must be absorbed on a hub (the well-known diminish period of Map reduce or anther comparative for greatly paralleled programming models). Be that as it may, the last osmosis stages for an extensive number of utilization cases have almost no data contrasted and the crude data

handled in the hub nearby errands. Consequently, the impact of this system overhead is for the most part (yet not constantly) immaterial.

3.19 SEQUENTIAL READINGS PREFERRED ON RANDOM READINGS

In the first place, you should see that how is the data seen from the circuit. The data must be situated as the plate head should be on the circle. This procedure, which requires some investment, is defined as the look for a task. When the plate head is situated as required, the data is perused off the circle consecutively. This is known as exchange activity. Look for time is roughly 10 milliseconds; Exchange rates upon request of 20 milliseconds (per 1 MB). This implies on the off chance that we were perusing 100 MB from isolated 1 MB areas of the plate, it would cost us 10 (look for time) * 100 (looks for) = 1 sec, moreover to 20 (exchange rate per 1MB) * 100 = 2 sec. This is an aggregate of 3 sec to peruse 100 MB. Be that as it may, in the event that we could peruse 100 MB consecutively from the circle, it would cost us 10 (look for time) * 1 (look for) = 10 mile seconds + 20*100=2 sec, for an aggregate of 2 seconds. Observe that we have utilized the various numbers dependent on Dr. Jeff Dignitary's location. In fact, the numbers can be changed; truth be told, they have improved from that point forward.

Apart from that, the relative boundaries between the numbers did not change, so we could use them for uniformity. Most large-scale data-programming models of this component are misused this component. Data is cleared consecutively off the plate and sifted in the fundamental memory. Balance this with a regular social database the executive's framework (RDBMS) show that is substantially more random– perused arranged .

3.20 BIG DATA PROGRAMMING MODELS

The main real types of Big Data programming models we will face are:

1. Large Parallel Database Framework (MPP): IBM.
2. MapReduce Frameworks: These frameworks all about Hadoop, which are the most global frameworks for all big data frames.
3. BSPs: The precedents include Apache HAMA and Apache Giraph.

3.21 Large-scale Parallel Processing Database Systems (MPP)

At its center, MPP frameworks utilize some type of part data dependent on qualities contained in a segment or a lot of sections. For example, in the previous model in which transactions were registered for 2000 organized by the State, We were able to understand data by type, so some methods may contain data for particular situations. This package strategy will enable each center to register absolute transactions for the year 2000. The barrier of this frame must be intuitive. You have to choose how the data will be part of the configuration time. The selected part criteria are often triggered by the hidden use state. All the things that have been taken into account, it is not reasonable to ask questions improvised. Some questions will be executed very quickly as they can take advantage of how data is part of the axes. Others will work at sliding speed in the light of the fact that the data is not reliably appropriate with how the question that brought the data was implemented and should have been shared with the hubs across the system .

To deal with this confinement, usually for such frameworks to store the data on various occasions, part by various criteria. Building on the question, the integrated data set is selected. Here is how the MPP programming model meets the characteristics of large data frames:

•Data is part of the state on independent hubs .

•every axis holds all the necessary apps of the libraries to capture an image in the sub-dataset.

•Each axis tracks the data itself. An exception is a point where you apply a question that does not relate to how the data is transferred; for this situation, each undertaking needs to bring its own data from different axes across the system.

•The data is viewed respectively for every task. Each of the business data is established and scanned from the painting. The channel (year = 2000) is connected in memory.

3.22 IN-MEMORY DATABASE FRAMEWORKS

From an operational point of view, database frames in memory cannot be distinguished from MPP frameworks. The usage distinction is that every hub has a lot of memory, and most data is preloaded

into memory. SAP HANA works on this guideline. In the middle, the database in memory resembles the MPP database in memory with the SQL interface. One of the real drawbacks to using business databases in memory is having a piece of equipment and comprehensive programming. Likewise, given that the frameworks utilize exclusive and exceptionally concentrated equipment, they are normally costly. Attempting to utilize item equipment for in-memory databases builds the measure of the group in all respects rapidly.

4. COMPARISON OF SCHEDULING

4.1 INTRODUCTION

With added data each day, it becomes a necessity to process it in petabytes. According to Cisco, just the amount of data from phones hit a record of 11.16 Exabyte's each month in the year 2017. Such data needs various forms of processing, like real-time, which affects context-specific uses and analyses to obtain important data.

Multi-V – that is, volume, velocity, variety, veracity, and value – usually explains the requirements to handle Big Data. In detail, volume refers to the amount, velocity to the rate of handling, variety to the different kinds, veracity to trustworthiness, and value to the significance in case of certain objectives to be achieved by data. Scheduling is paramount in making the most of Big Data optimization, mainly to economize in the time. It focuses on organizing and fulfilling a maximum number of jobs related to data with the most effectiveness and least migration. To assign resources, one can apply many tools in cloud, high performance computing (HPC), grid, and peer-to-peer systems, all having non-similar architectures. HPC for instance uses clusters to handle data in homogeneity and in line with using pre-arranged rules. Cloud, on the other hand, may have heterogeneity and extended spread. Here, task operations know of these rules and provide the chance to even form specific ones intended for scheduling, whose real applications in Big Data comprise the following: first in first out, fairness, capacity, Longest Approximate Time to End (LATE), deadline constraints, and adaption.

It is vital to seek out most appropriate ways for specific processing, and one may observe that this task in Big Data is done in the form of batches with HPC clusters that divide them to smaller ones and among many nodes. Other recent uses, such as social networking, graph analytics, and detailed business work lows, need to move and save data. In this respect, different models have to know the place of data in order to transfer them to nodes or form new nodes around the place. To make efficient task completion requires strategies to make sure resource suppliers benefit from top capacity use. In case of areas of use hard in terms of workload and computation, these models mix various strategies including in-memory, CPU, and graphics processing unit (GPU). What's more,

tools in Big Data have a heterogeneity issue thanks to different distributed types, such as clusters, grids, cloud, and peer-to-peer intended indeed to back up complicated operations.

Once merged with other distributed platforms, in Big data such planning techniques should also bear in mind other alternatives to tackle problems and parallel data transfers – in fact, those do not reveal latency – while applying other mechanisms to deal with failures in non-homogenous settings. Furthermore, such non-homogeneous sets turn into problems as concerns interoperability in alternative other software.

The present chapter looks into the main requirements for Big Data scheduling, algorithms, data transfer processes, principles followed by various computations, and finally optimization. In the end, a case study is presented for Hadoop and Big Data along with defining new ways to merge New Structured Query Language (NewSQL) databases with such distributed file systems and computations.

4.2 REQUIREMENTS FOR SCHEDULING IN BIG DATA PLATFORMS

In case of conventional models, these are based on applications, databases, and storage resources, all of which have multiplied in time, adding to the expenditure and complications associated with them and, hence, calling for improvements in storage, analyses, and availability. The conventional approach is now getting a face-lift to contain other components to refer to these difficulties and new structures for Big Data. While combining the use and operations of these tools, one needs a layer to control cluster resources; other specific planning and operational engines are also needed for certain approaches, mainly batch tasks, data low, NewSQL tasks, and others.

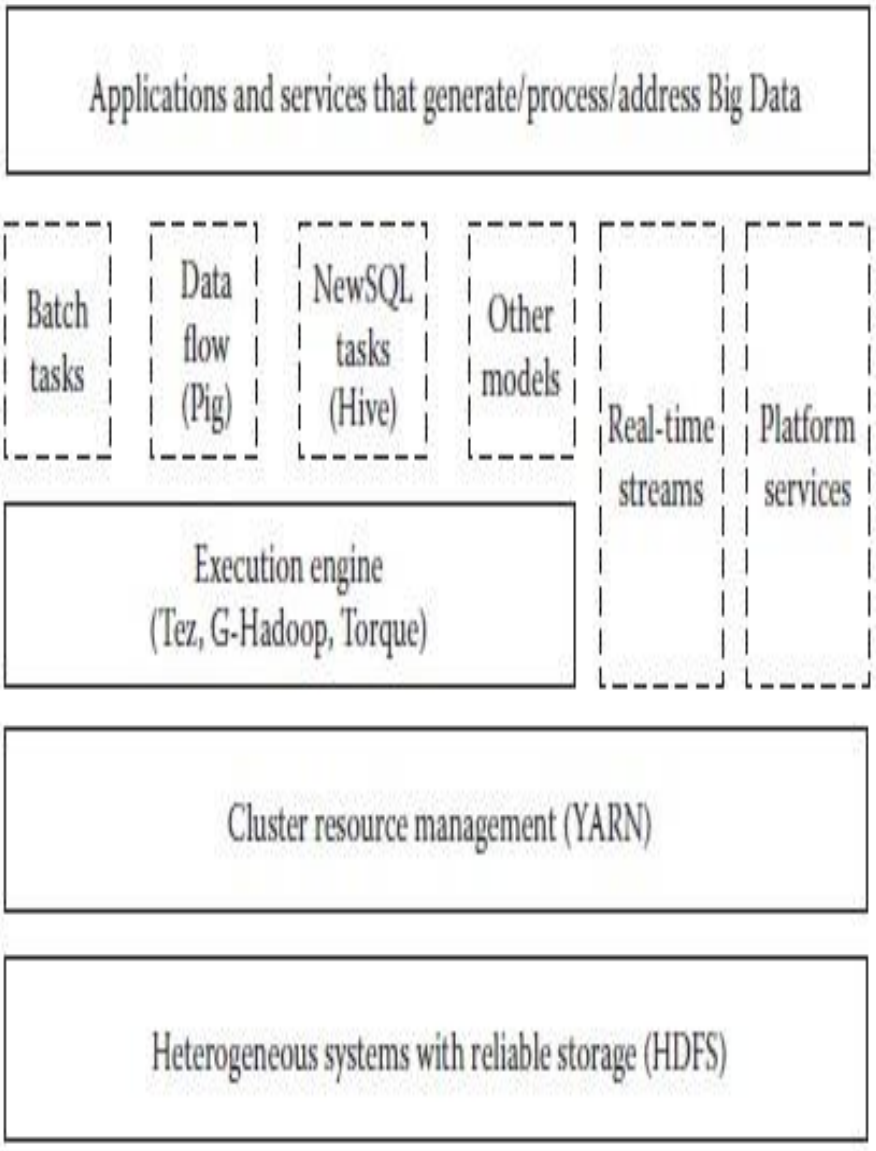

Figure 4.1: Big data platform integration for application

The overall conditions to schedule Big Data address both operational and non-operational features necessary for scheduling. In what follows, we will look at these:

4.2.1 SCALABILITY AND ELASTICITY

An algorithm for scheduling has to deal with data in peats and countless processors for the purpose. For this reason, the scheduler needs knowledge of transformations in the environment and the ability to adjust to them in the form of supplying or cutting back on resources.

4.2.2 General Purpose

Any scheduling has to predict and apply certain limits for certain uses. Interactive jobs, distributed and parallel applications, and non-interactive batch tasks need to be backed in terms of operations. . To illustrate, a batch job of this nature that needs maximum throughput might choose time-sharing for scheduling. In the same way, a real-time task needing a quick response may choose space-sharing for the purpose.

4.2.3 Dynamicity

The related algorithm has to maximum use of resources and alter its patterns to manage, numerous jobs, to give an example. Scheduler require constant adjustment to amounts of the resource at hand, and use the cloud and HPC clusters or centers for trusted alternatives to be used in Big Data.

4.2.4 Transparency

Hosts where operations are in progress may not influence tasks behavior or outcomes. According to users, no difference must prevail between local and distant operations, with users' full awareness of any changes or movements in Big Data concerning the system.

4.2.5 Fairness

Spreading even amounts of resources ensures each user's supplies as per requested. The pay-per-use model allocates a cluster of resources or saves it for later use in Big Data.

4.2.6 Time Efficiency

Schedulers have to optimize job arrangements to the maximum with the help of heuristics and status estimates needed for certain jobs. Here, multitasking mechanisms are able to handle many sets of data simultaneously through mapping to resources to make the most of their application.

4.2.7 Cost Efficiency

Schedulers have to reduce operational costs through reducing the resources applied within the allocated budget. Such economizing calls for the use of older resources, possible through improving the execution for multi-faceted jobs with advanced queuing as well as by decreasing costs related to computation and correspondence.

4.2.8 Load balancing

Load balancing is a way to spread the load throughout the resources at hand, and can be difficult if there is no conformity between task features and the resources. Conventional methods, namely round-robin scheduling, and new ones dealing with extended and non-homogeneous systems for this include least connection, slow start time, or agent-based adaptive balancing.

4.2.9 Support of Data Variety and Different Processing Models

This is possible in the form of dealing with numerous and simultaneous tasks and streams, (non)organized content, multimedia, high-level analyses, job arrangement as big or small, more or less urgency, or periodic and non-periodic.

4.2.10 Integration with Shared Distributed Middleware

A scheduler has to address different and middleware structures, including sensor integration anywhere upon the emergence of the Internet of things even in the case of alternatives for mobile cloud where offloading is often employed to cut down on energy consumption. Such deployment

takes into account availability of data and its use, while responding to different workloads generated through applications.

4.3 THE HADOOP SCHEDULING ALGORITHM

This is among the basic applications of Hadoop platform mainly to run the jobs and designate them as per the available resources. Hadoop makes possible advanced data processing for distributed nodes; it remains a multi-functional mechanism able to manage many data sets for many task and many users all at the same time. Such a facility implies the opportunity for better mapping of resources and optimizing such an application as a result. Next, Hadoop jobs distributes cluster resources as per a structure for contrivance for the time and place of any job to be operated.

Many forms of application for this platform are distributed among numerous users, and this figure keeps on growing. Accordingly, numerous mixtures of long batch tasks and short interactive ones reaching similar data sets are no now common among the jobs being run. Based on this, within non-heterogeneous settings, multi-user algorithm mainly intend to maintain balance in cluster proficiency and resource allocation dexterity. Scheduling here minimizes closure time, improves throughput, lower the costs, and moderate the resources for concurrent uses in the form of proper allocation of different tasks to processors. Most aim to change data locality and some others apply synchronization. Since plug-in schedulers are used, numerous algorithms are created some of which will be introduced in the following.

4.3.1 FIFO Scheduling Algorithm

FIFO mainly aims to arrange tasks as per priority. Hadoop by default applies FIFO, which means “first in, first out” to select waiting jobs at Job Tracker in the line with no attention to order or dimensions. Based on the priority and time once selected, all lines of job are examined and later a manageable one is taken up to be completed FIFO technique, being straightforward, is applied once the order of completion is of no importance. Some limitations do prevail, of course, as the algorithm targets one kind of job and if many users simultaneously apply many jobs, the efficiency may remain low as a result. Given the increasing application of Hadoop, demand can become more as

well. The algorithm minimizes total functionality and resource uses, and sometimes may even affect job completion.

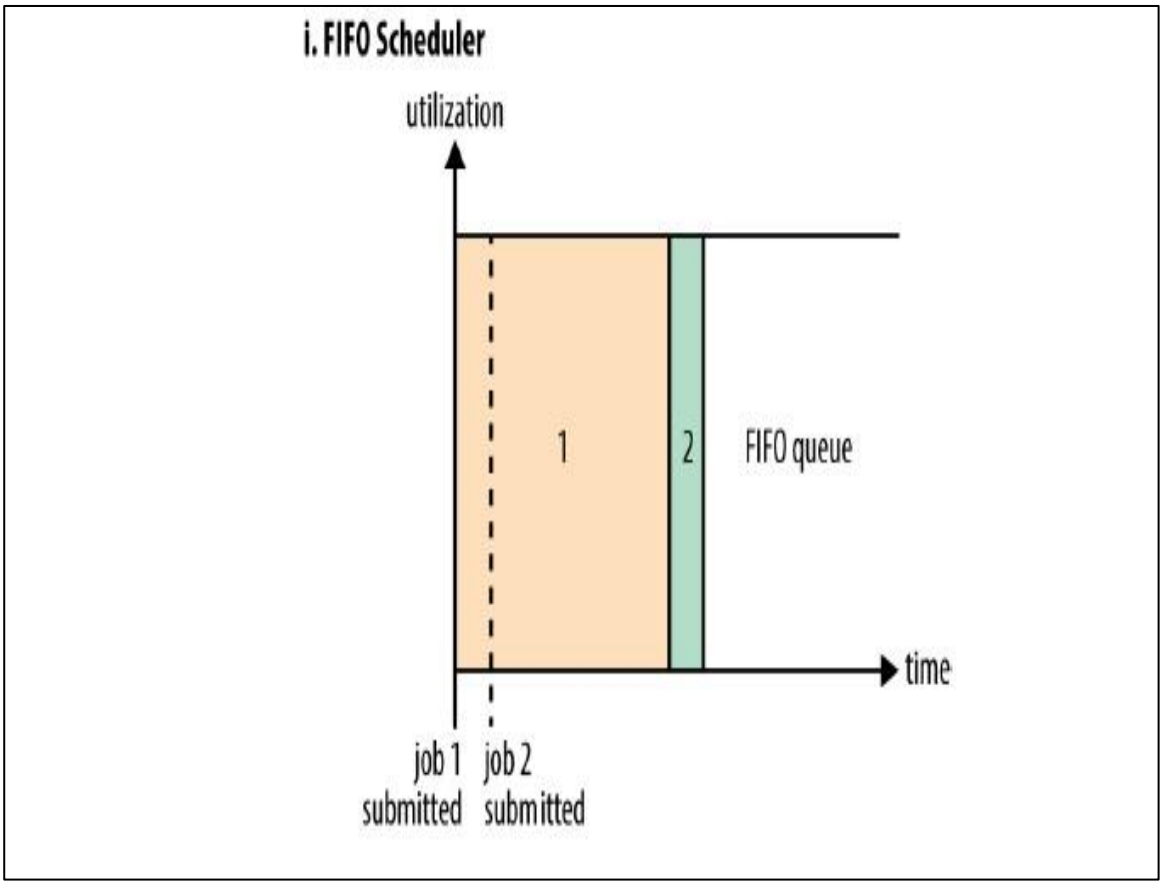

Figure 4.2: FIFO scheduling mechanism

4.3.2 Fair Scheduling Algorithm

This algorithm monitors access to resources as a whole to distribute even amounts to all jobs at hand at any given time. Created by Facebook, the idea behind this system is resource allocation fairly within time. Consequently, jobs requiring less time can reach the CPU to be carried out while others requiring more time are being done. This process reduces interactivity among jobs and burden the cluster even further to allocate different job types. Fair scheduling makes even distribution of resources possible among all users and jobs within the system by commonly arranging jobs in pools and sharing all resources evenly among these pools.

Such even allocation is carried out with the MapReduce task slot. Once free – that is, if not in use – then the inactive slot of a pool is applied by others. If, for example, a user or pool sends many jobs, then the scheduler may restrict them by rendering them inoperable. The system works on job taxonomy scheduling in a way that different jobs gain different resources, hence service quality is improved and paralleling number actively adopted accordingly. The system makes the most of the resources and improves system usability. Fair scheduling is arranged in the mapred-site.xml file, which defines all specifications running the scheduler's behavior.

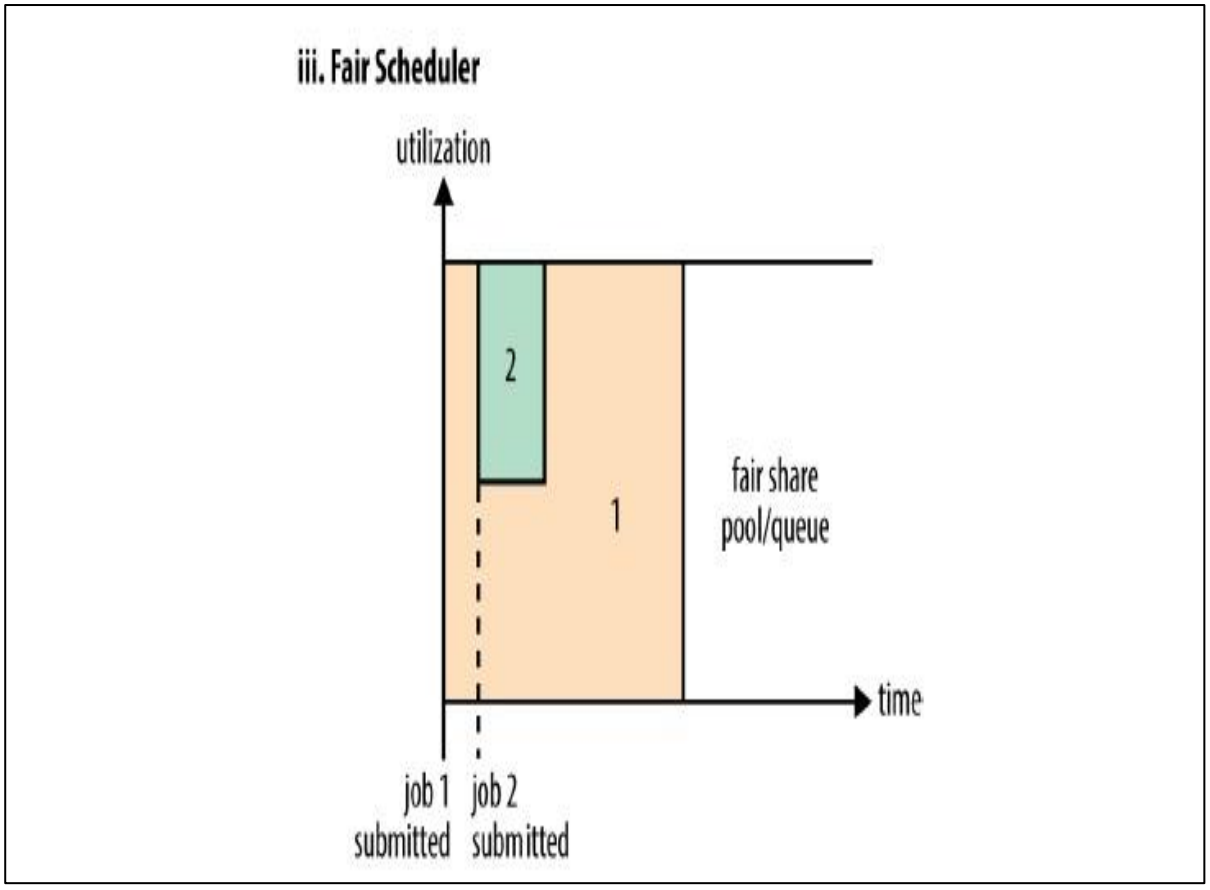

Figure 4.3: Fair scheduling mechanism

4.3.3 Capacity Scheduling Algorithm

This system operates the Hadoop applications in the form of shared, multi-tenant clusters within an operator while increasing throughput and cluster use. This scheduler was mainly created by

Yahoo for increasing resource utilization within cluster settings by sharing. It has the same principles as Fair scheduler but different other features. Namely, capacity scheduling is intended for large clusters with numerous independent users and applications. Henceforth, this tool offers better monitoring and also enables minimum capacity insurance to divide extra resources among other users. This is done by lining up and not compiling or pooling, with each line assigned to a system and the resources spread among them. In a sense, the algorithm takes into consideration the status while queuing, and then assigns a fixed capacity for each line. Should any line receive excess load, the scheduler finds unused resources and assigns them fairly to each task.

In order to make the most of resources, once a line is not using the given resources, the extra resource may be given to others. With new arriving tasks, resources become re-assigned to the front lines once the latest ongoing tasks are over. A separate point about this type of scheduling is the possibility to order the jobs in a line as deemed necessary. Under ordinary circumstances, those being urgent get the resources first than those least urgent.

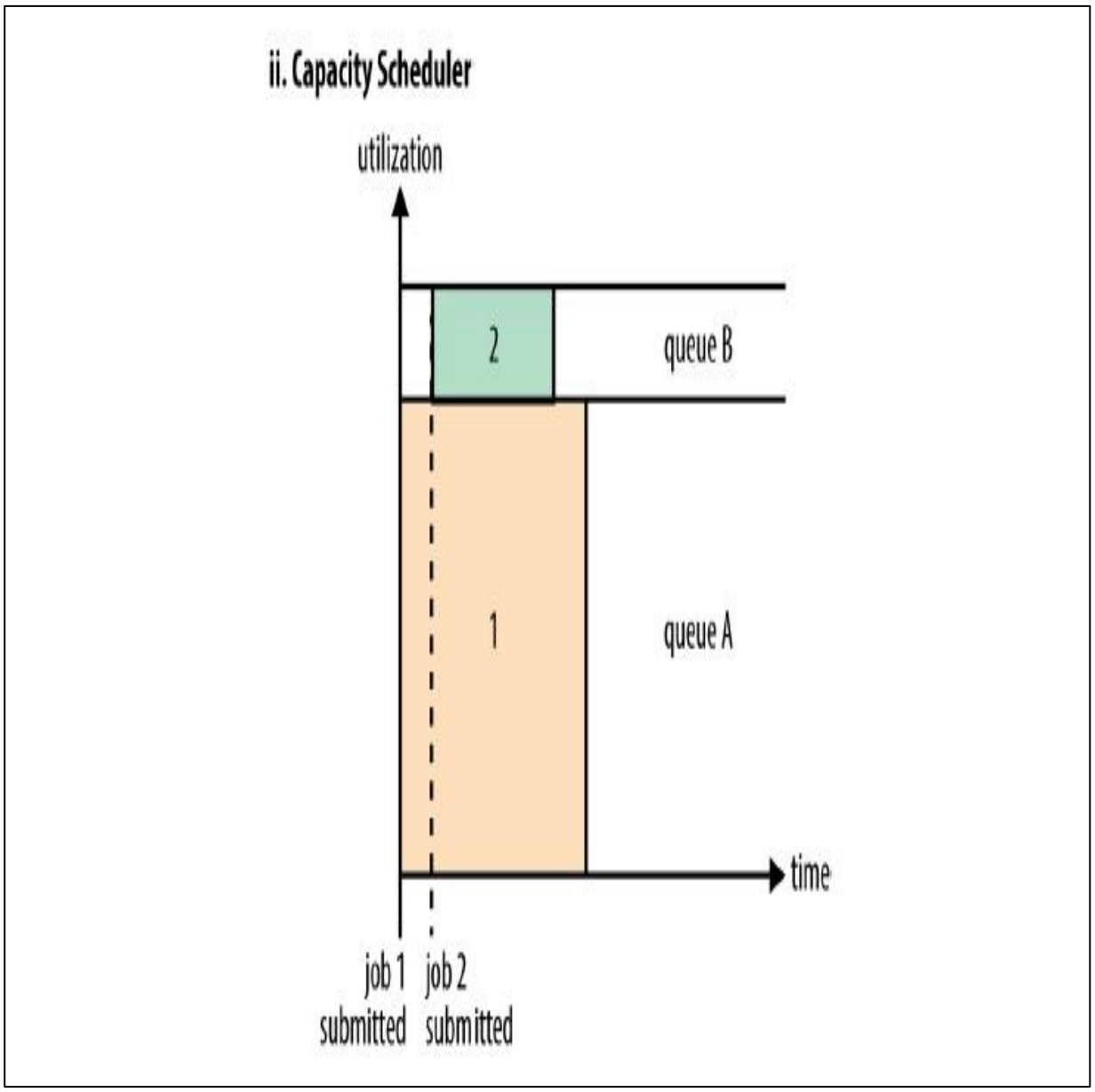

Figure 4.4: Capacity scheduling mechanism

4.3.4 Delay Scheduling Algorithm

This utility is for now used in fair Scheduler within Hadoop. As Fair scheduler applies a dual-layer system, where every user possesses a certain pool within one joint cluster with the least portion allocated to each pool. Numerous tasks within each pool use the same time slots. Throughout the

pools, this slot varies in size and the level of fairness is assessed. Least share comprises the smallest slots to be allocated; should these slots remain unused, then other pools may make use of them instead. Should there be none left causing deprivation by user, then there will be pre-emption – in other words, slot re-allotment but other tasks to the user needing it the most.

In itself, pre-emption occurs in two ways: either by terminating jobs in progress right away, or by awaiting completion of jobs. The former wastes the time allotted for running those jobs, while the latter is a disproportionate use of fairness. Delay scheduling applies waiting to increase locality since to re-arrange a job formerly given to another user means a missed chance to equip the jobs on each node with data. This approach does not quickly re-arrange a task for uneven jobs, but rather does so in a while in order to increase locality and flexible fairness.

In addition, the approach handles other related issues like head-of-line scheduling as well as sticky slots. The former takes place once insignificant jobs are allocated to nodes in the absence of data; whereas the latter relates to sooner completion of tasks and the job remaining in the original slot. Sticky slots often emerge in case of larger jobs. Here, the advantage is in gaining even distribution on top of further developing locality through adapting the level of fairness and not attempting to assign jobs in a solely greedy way. In the end, this scheduling reduces the extra burden of moving costs over the network.

4.3.5 Context Aware Scheduling Algorithm

According to a model is available for intelligent operations mixing context awareness and adaptive scheduling methods. There, the priorities for jobs within servers are arranged to deal with changes in the local settings of end-users with the aim to operate in response to delays within mobile settings, as well as to minimize undue use of resources by appropriate arrangement of all tasks within the Cloud. Put differently, by means of fixing the order of arriving jobs in proportion to changes within the local settings, total use of resources is maximized, operations are better, and finally better quality of service is re-assured.

Suggested by Kumar et al. the context-aware scheduler (CASH) which applies available heterogeneity in clusters combined with the workload to optimize jobs by making use of similar

sets of data. In this system, operations in non-homogeneous Hadoop clusters are developed and, despite remaining in a state of simulation, the scheduler offers improved operations thanks to exploiting all nodes within the cluster. The approach use two main schemas: the first one is that a majority of MapReduce tasks are carried out in periods and share the same average features as to CPU, network, and disk requirements. The second aspect is that nodes within Hadoop clusters turn non-homogeneous in the course of time as a result of failures, and that is when new nodes are put in place. This algorithm is designed for this purpose, with due regard for job specifications as well as accessible resources in nodes. Next, within 3 steps it completes its jobs; these are: by grouping jobs as destined for CPU or I/O; grouping the nodes as either computational or I/O; and finally mapping the jobs as per various the needs to nodes capable of doing so. The use of CASH allows for heterogeneous cluster management and maximizing job completion given the time.

4.3.6 Deadline Constraint Scheduling Algorithm

This utility deals with time constraints, and mostly on improving the use of the system. Time limits mentioned by users once arranging the jobs ensure completion within the stated periods. The focus is mainly on due time by handling with the related needs according to the cost model for execution – that is, bearing in mind factors like the size of input, map and reduce completion time, data distribution, and others. During the arrangement of any tasks, each is scrutinized to see if it can be finished within the allocated time. This scheduler operates as follows: first, different and separate periodic jobs are assessed in one group; next, once the resources exceed the capacity of data center, task movement among different locals simply takes care of the whole deadline; third and last, within non-homogeneous settings, additional resources are given to the same demand in according to time restrictions.

4.3.7 Matchmaking Scheduling Algorithm

C. He, Y. Lu, et al. propose a different matching algorithm to process the rate of data locality and approximate repercussion in MapReduce clusters. Matchmaking scheduling attempts to make data locality better in mapping with the overall motivation to assign each slave node an equal chance to take on local jobs before non-local ones are assigned. A local task runs on the node with accessible

data. This algorithm detects matches once, for example, slave node Int. J. Adv. Res. 6(3), 241-258 takes on input. Not all map tasks are assigned and each node is highlighted with a location reference to ensure receiving a fair opportunity to get local tasks. Finally, each slave node locality marker is removed with arriving jobs new in line. In this way, such jobs might have local tasks for certain nodes, and once new ones arrive, the scheduler resets the settings for all nodes and, hence, the so called all-to-all task-to-node matchmaking resumes once again.

4.3.8 Enhanced Self Adaptive MapReduce Scheduling Algorithm

This scheduler is intended to re-do sluggish tasks in MapReduce. Here to identify such tasks in a proper way, background platform weights are classified on each node end into K clusters with a K-means algorithm once performing the tasks on each node. The outcome goes into a cluster to apply its weights so as to estimate the time needed for tasks. ESAMR can check whether the error in the small tasks and re-executed again. On the other hand, machine learning is employed to group background information on nodes and each node into k clusters. For example, if job in progress is done with mapping, then ESAMR saves the job's non-permanent map phase weight on the node depending on the assigned tasks and applies these weights to find any cluster with the most similar weight.

4.3.9 Self-Adaptive Reduce Scheduling Algorithm

Proposed by Z. Tang, L. Jiang, et al., this one aims to scrutinize maps and decrease the stages as it can effectively indicate the start point of reduced tasks as per the output of map tasks. It also increases best use for resources by reducing the anticipated time for task completion. For starters the number of tasks is reduced each map output is monitored on data blocks – otherwise known as the copy phase. Next, such outputs are organized into memory data and circular buffer data. The memory intended to reduce tasks is restricted, hence the reason for buffer data to be periodically reflected on disk. In exterior sorting, new data should merge with this on-disk data as often. In case of excessive map jobs or extended ones, there is a need for exterior sorting numerous times and also copy and sort in the meantime – also known as the shuffling stage. With this scheduler the

approximate response time can drop by 12% to 30% in case of common applications like capacity scheduler, FIFO and fair scheduler.

4.3.10 COSHH Scheduling Algorithm

Formed by A. Rasooli, D.G. Down, et al. this new algorithm is used in Hadoop by maintaining heterogeneity in cluster and also in application. COSSH mostly aims to apply system information and decide on scheduling in a way to improve the overall operation of the system. There are two steps: designating jobs in appropriate lines once new ones arrive, and doing so instantly and according to free resources. Routing is initiated by the scheduler to assign jobs as per the available resource mainly to shorten the completion time.

4.3.11 Longest Approximate Time to End (LATE)

Jobs in general take long to complete, partly due to CPU overload or sluggish operations in the background. In all, a job is completed only once different tasks are so. LATE finds such slow tasks and initiates a similar one for support – a process known as speculative execution. With the backup version finishing earlier, time and operations are improved, which means that this feature is a method to optimize and not guarantee reliability. In case of slowness due to code faults, LATE cannot be beneficial as identical faults can also impact speculative operations. To tackle this problem, debugging is necessary. In addition, the method depends on a certain degree of guess work related to uniform task progress on nodes and the computing environment. Consequently, speculative execution functions better in non-heterogeneous clusters as they are related to real-world issues. Zaharia et al [6] offer LATE, which makes use of the extra time to finish task instead of allowing it to be done by the task itself – which approach has shown major optimization of response time within default speculative operations.

4.3.12 Resource Aware Scheduling

The Fair Scheduler and Capacity Scheduler, as stated earlier, intend to provide even capacity allocation among users and jobs regardless of the available resources as a whole. Since the CPU

and disk channel capacity has continued to expand recently, Hadoop clusters with non-homogeneous nodes may experience major changes in terms of processing power and disk access speed for the nodes, leading to decline in performance in case of numerous processor-heavy or data-heavy jobs designated to nodes with sluggish processors or channels. This situation can worsen in case the Job Tracker takes each Task Tracker node with a certain available number of slots. Under these circumstances, even an optimized LATE operation can exacerbate the task congestion in any occupied cluster by merely giving speculative copies to slots on the verge of maximum resource use.

Resource Aware Scheduling in Hadoop is now a major field to address in Cloud Computing as scheduling in this environment is oriented and based on initiation by worker. Related actions are taken a master node, known as JobTracker, with worker nodes or TaskTrackers completing the tasks. The JobTracker sets up a line of presently active jobs, the status of TaskTrackers within one cluster, and also a series of tasks assigned to each one of them. Next, Task Tracker nodes are readily created with the highest amount of computation slots as possible. This can, though, be also managed for each node so as to demonstrate the actual processing power and disk channel speed, and other features within the cluster, the accessible slot capacity may also be attained online. In other words, congestion may not decrease upon demonstrating limited capacity. In this way, each Task Tracker node examines the available resources like CPU utilization, disk channel, IO in bytes/s, and page faults per unit of time for the memory subsystem. Despite other factors also being possibly helpful, these are suggested as the three main sources of supply to be followed constantly so as to maximize even loading on cluster machines. Specifically, the loading on disk channel may exert greatly on data loading and the writing segment within Map and Reduce tasks, even far exceeding that of the accessible space. In the same way, the original ability of a system's memory status implies that controlling errors on pages and disk thrashing is perhaps a better way to predict the amount of load than and monitor free space.

There are two scheduling ways by resource-aware Job Trackers:

1) Dynamic Free Slot Advertisement. Rather than using a certain amount of accessible slots arranged on each node within Task Tracker, the amount is measured actively with the resource

measurements taken for each node. Within an alternative heuristic, the total resource at hand is determined on system as the lowest amount throughout all metrics. Where a cluster may not necessarily be active at top capacity, such a technique makes the response time much better since no system will then face bottleneck situations.

2) Free Slot Priorities/Filtering. This technique allows for cluster managers to set most of the slots in each node for the period of configuration with priority in a way that the idle ones in TaskTracker are advertised and arranged as per access to resource. Since these slots are not occupied, buffering will take place for a short while, for example two seconds, and then advertisement occurs in a series. Those with more availability are taken first for scheduling to take place on them. Within settings that require small tasks to last long before completion, this attempt can greatly improve the operations. Rather than scheduling on subsequent idle slots and consuming too much resource, response time is reduced by doing so on slots containing much resource and regardless of the added time for nodes to be accessed. Buffering the advertisement of free slots allowed for this scheduling allocation.

4.3.13 Maestro Scheduling Algorithm

Maestro can detect copies and is proposed by S. Ibrahim, H. Jin, et al., deferring the challenges of scattered tasks which rely on task copies from map. It follows the places of chunks and duplicates as well as others within nodes to initiate the jobs with no impression. In this way, vacant spaces within nodes are made full according to the number of tasks and those contained within the incoming data duplicate schemes. The possibility for lining up a job according to its copies on a system, the operational schedules are assessed and done within two ripples: one is to stow the vacant slots within data nodes as per the map tasks, and also on the copied schedule for their input data. Another one is that scheduling occurs upon the chances of arranging map jobs on machines based on the copies of their data. Both ripples yield better locality when operating tasks.

4.3.14 Hybrid Scheduling Algorithm

Proposed by H. Nguyen, T. Simon et al., this method entirely renews the response time in case of numerous Hadoop settings mainly to actively prioritize and, as such, decrease the time for completing jobs with different periods required and occurring at the same time, thereby changing arrangement to maintain locality. Furthermore, the algorithm considers user-defined values at5 the service level in terms of its quality as it is created for data-heavy jobs. The app. time needed for workload is about 2.2 times better in Hadoop Fair with a criterion deviation of 1.4x. Such superb speed is gained as it adjusts the degree of fairness using an exponential model.

4.3.15 Energy Aware Scheduling

In a greedy scheduler is introduced and named Energy-aware MapReduce Scheduling Algorithm (EMRSA) designed to make energy use in related applications more efficient and meet the SLA conditions. It finds map assignments and decreases the tasks within the slots to reduce the use of resources once in operation and arrange each job in a way to meet the expected due date. Tasks are operable at the same time, yet no reduction may be initiated unless all is completed within the application.

Chen et al. came up with an approach for MapReduce without the need for copying and, instead, separating jobs to time-critical and lower time-critical. The first one is allocated to group of assigned nodes, and the second one may simply operate on the remainder of the cluster. In addition, it can minimize resource use. According to Land and Patel, another approach for MapReduce clusters can save resources in the form of reducing power on all cluster nodes while operations are not intensive. EMRSA can detect schedules with roughly 40% less consumption compared to those commonly in use.

A point to remember in MapReduce Schedulers is that users simply do not indicate deadlines for the map phase. Still, since reduce tasks rely on those in the map, the data center decides on a fair due time for them in accordance to slots accessible so as to make them most of the resources.

4.3.16 Dynamic Priority Scheduling

This algorithm designates order of execution in terms of factors and improves the use of resources. Thomas Sundholm et al came up with this scheduler to back up active division among simultaneous users as per order. Automatic designation of resource and re-designation take place based on market for task assignment within a defined task slot resource market. Users are given a certain portion of virtual money, and throughout job handling, they may announce a fixed amount of resource use for a period. The scheduler finds tasks with the most income. Users may change their payments so as to change the order of completion in their own favor. This can be done solely by themselves with the system giving time to them based on how much time they use. Should the balance of expenditure and gain hit 0, then task assignment ceases, allowing users in this way to obtain either a Map or Reduce space based on proportion for each unit of time. Such time slots are labelled allocation interval and may be arranged accordingly for 10 Seconds to 1 minute.

Let's imagine a top 24 Map slot capacity for 3 users equally. One asks for $5 and receives 5/ (5 + 4 + 3) * 24 = 10 slots. Here, Dynamic Priority Allocator checks and executes the transaction via the central scheduler. The method is ideal for small jobs and larger ones alike. Yet, Hadoop MapReduce tends to reduce large-scale jobs to ensure a limited number of spontaneous jobs using equal amounts of resource. To prevent short supply, bottlenecks in line, and satisfy all changing requests as fast as possible, pre-emption is an option for the allotted slots to be given to other users if remaining idle for a while.

Thanks to the method of price changing, all users receive a guaranteed slot against more payment, hence reducing the likelihood of free-loading and gaming. The Hadoop MapReduce scheduling makes more detailed division possible for tasks repaired automatically upon faulty completion. No need for users to be concerned about task completion as average capacity will be used for a while for processing and making the due deadline.

SLAs, like setting up deadlines, are important as they propose resource allocation decisions. The standard Hadoop restricts the time required for each job to be completed on nodes and, in this way, eliminates the likelihood of starvation for less-important ones. System management may utilize

this feature to fix allocations and determine pre-emption for running tasks, or alternatively take no action until the user's budget is finished. In this way, numerous cases of starvation may be avoided by Hadoop by means of arranging tasks within slots and not at the job level.

Additional expenditure will not be necessary given the additional idle slots to assign tasks. This is the outcome of economizing on the workload as a principle adopted by this algorithm. No assurance is ever given to keep extra resources because the aim is to see the reaction of new users giving jobs. If one of them recognizes steep costs, he might wait before the job is pre-empted. In the meantime, should the resources be offered with no return, numerous other resources may be asked for in no time at all.

Table 4.1: comparison of the scheduling algorithms

Algorithms	Technique	Advantage	Disadvantage	heterogeneous	Homogeneous	Taxonomy	Mode	Sticky Slots	Priority in job queue	Job allocation	Fairness/ Fair sharing of Resources
FIFO [1]	Schedule jobs based on their priorities in first come first- out.	1.Cost of entire cluster scheduling is less 2.Simple to implement and efficient 3.Because of lack of dissension within the nodes for multiple clients' job it enhance	1.Designed only for single type of job 2.Low performance when run multiple type of jobs 3.Size of the job or priority are not given any importance		Yes	Non-adaptive	Non Preemptive	NA	No	Static	No

		The performance. 4. Poor Locality 5. Poor utility									
Fair scheduling [27]	Do an equal distribution of compute resources among the users jobs in The system. Allocate equal shear of Resources to each job.	1.Less complex 2.Works well when both small and large cluster 3.Furnish fast response time for small tasks Mixed with large tasks. 4.It sets the bounds to the number of	1. not consider the job weight of each node 2.Job size is Completely ignored.		Yes	Adaptive	Preemptive	Yes	Yes	Static	Fair share of the cluster capacity over time

		associate jobs In every job pull.									
Capacity [28]	Maximization the resource utilization and throughput in multi-tenant cluster Environment**.**	1.Ensure guaranteed access with the potential to reuse unused capacity and prioritize jobs 2. Unused capacity used by jobs in the queues.	1. The most complex among three schedulers. 2. Does not consider resource availability on a fine-grained Basis.		Yes	Adaptive	Non Preemptive when job fail	NA	No	Static	Yes

LATE [29]	find out process running with slow speed in the cluster and create equivalent process in the background as a backup	1 Robustness to node. 2. Optimizes the performance of jobs. 3. Minimizes job response time. As much as possible.	1. Poor performance due to the static manner in computing. 2. Lack of reliability.	Yes	Yes	Adaptive	Preemptive	NA	Yes	Static	Yes
SAMR	To improve Map Reduce in terms of saving the time of the execution and the system's resource.	1. Decrease the execution time of map reduce job. 2. Improve the overall map reduce.	1. Do not consider the data locality management for executing backup task.	Yes		Adaptive	Preemptive	Yes	Yes	Static	Yes

Hybrid scheduling	Designed for data intensive workloads and tries to maintain data locality during job execution	1. Fast And flexible scheduler. 2. Improves response time for multiuser Hadoop environment.	1. The time taken for the creation of tasks and result retrieval is increased due to the increase in the number of tasks.	Yes	Yes	Adaptive	Preemptive	NA	Yes	Static	Yes
Maestro	Proposed for map tasks, to improve the overall performance of the Mab reduce computation	1. Provides higher locality in the execution of map task. 2. Provide more balanced intermediates data distribution for the shuffling phase.	1. There is a delay in performing the task compared to FIFO.		Yes	Adaptive	Preemptive	NA	Yes	Static	No
Delay scheduling [30]	Queue based scheduling	1. Simplicit	1. Relaxes fairness		Yes	Adaptive	Preemptive	NA	Yes	Static	NO

	relaxing for locality Enhancement.	y of Scheduling. 2. No Effect of complex Calculations.	slightly. 2. Not effective if a large fraction of tasks is much longer than the average job or there are few slots per node.								
Dynamic priority Scheduling	In order to balance current workload it allows users to enhance or diminish their queue Priorities.	1. Configured easily.	1.In the event of crash of system all incomplete low priority processes Gets lost.	Yes		adaptive	Preemptive	Yes	Yes	Dynamic	Yes

	Supports the capacity distribution dynamically among concurrent users based on Priorities of the users.										
Deadline constraint Scheduling	It concentrates on the deadline constraint of task which denotes the problem of deadline but	1. Supports optimization of Hadoop Implementation.	1. Cost incurred for each node should be Uniform. 2. Difficulty in finding execution	Yes	Yes	adaptive	Preemptive	NA	Yes	Dynamic	Yes

	mainly helps in enhancing System utilization.		timing cost.								
Enhanced Self-Adaptive MapReduce Scheduling	For the speculative re-execution of sluggish tasks in MapReduce. In ESAME, in order to recognize sluggish tasks accurately.	1. Can identify slow tasks More accurately. 2. Improves the performance in terms of estimating task execution time and launching Backup tasks.	1. Little overhead due to K-means algorithm. 2. Allows only one speculative copy of a task to run on a node At a time.	Yes		adaptive	preemptive			static	
Matchmaking[22]	Gives equal chance to	1. Provides	1. Time spent in		Yes	adaptive	preemptive	Yes	Yes	Static	Yes

	each slave node to seize local tasks before assigning slave node with non-local tasks.	highest rate of data Locality. 2. Good data locality and utilization when find matched Data quickly.	finding matched data will increase response time.								
Energy aware	Minimize energy consumption during execution of Map Reduce Job.	1. Optimization of Energy.	1. Multiple Map Reduce jobs.	Yes	Yes	adaptive	preemptive	Yes	Yes	Dynamic	Yes
Resource aware[31]	Uses two resource metrics: Free slot filtering and Dynamic free slot Advertisement.	1. Better performance of job. 2. Resource better utilization in cluster.	1.Need for additional capabilities to maintain Network	Yes	Yes	adaptive	preemptive	NA	Yes	Dynamic	Yes

			bottlenecks.								
context aware scheduler	Designed to execute the largest number of jobs, having roughly the same characteristics and execute at the same time.	1.Optimizations for jobs Using the same dataset.	1.Still in simulation stage	Yes		adaptive	Preemptive	Yes	Yes	static	Yes
COSHH [32]	Proposed to improve the mean completion time of jobs.	1. Improve the overall system performance. 2. Addresses the fairness and the minimum share requirements.	1. Search overhead.	Yes		adaptive	Preemptive	Yes	Yes	Dynamic	Yes

5. DISCUSSION AND CONCLUSION

5.1 INTRODUCTION

the main idea of this study is to fill the gap we are findings during the make research about Apache Hadoop scheduling algorithms, we conduct using Systematic Literature Review approach, in this thesis, we conduct a k.Petersen and et al [33] as a guideline to get the result. Whatever, Apache Hadoop has several kinds of scheduling algorithms namely Fair, FIFO, LATE, Delay and may other scheduler algorithms it fully discussed in Chapter 4 as individually. In additional, FIFO is the most scheduling algorithm is being studied in literature compare to other scheduler algorithms it was listed under the titles "Others". In the same way, we recommended different types of database to complete this study. Of the 221 papers, we found during the search databases that we are selected and by using search string it just 63 paper it was relevant to our study in both directions direct or indirect. However, in big data, there are different types of proposed these scheduling works in a different environment each one has own environment. The most case discussed of these environments it is Homogeneous and Heterogeneous, as can be seen in the Table 4 the cases and scheduler algorithms for both type that was discussed in a fully in Chapter 4. on another side, scheduler algorithms has also advantages and disadvantages that make an effect on the production and processing of data these things, we given in an extensive form. In the same side, a mechanism could also make an effect on the schedule for both pros and cons. Some of scheduling algorithms got an optimization and that make a new algorithm but in reality the mechanism it same.

RQ1: In which environment scheduler can be work good?

In big data there a lot of type of environment that can be on the type of infrastructure of the data and design of the hard-ware. There are different of cluttering in big data rely on the data that need to work on it. Scheduling algorithm it can be work in two types namely' Heterogeneous or Homogeneous'. Depending on the design of algorithm it can working in the cluster.in the Table 4 we showing these two type within all algorithms that is discussed in the previous Chapter. It maybe

homogenous and depending on my SLR the algorithms that can be under this part are “FIFO, Fair, Capacity, LATE, Hybrid, Maestro, Delay, Deadline, Matchmaking, Energy, resource. On the other hand, the second part is heterogeneous and the algorithms that can be under this part namely “LATE, SAMR. Hybrid, deadline, Enhanced, energy, resource, Context, COSHH”.

Table 5.2: Scheduling environment in different type of scheduling algorithms

Environment	FIFO	Fair	Capacity	LATE	SAMR	Hybrid	Maestro	Delay	Dynamic	Deadline	Enhanced	Matchmaking	Energy	Resource	Context	COSHH
Heterogeneous				×	×	×			×	×	×		×	×	×	×
Homogeneous	×	×	×	×		×	×	×		×		×	×	×		

RQ2: which type of mechanisms are being used for each algorithm in Apache Hadoop scheduler? Which one's dominantly using?

One of the most important thinks in scheduling algorithms is to know the processing and the mechanism are being used in each scheduling. That make researches and practitioners have a good knowledge using scheduling, thereby we make this thesis to know individually each scheduling algorithm what a technique used and what is the different between each of them. In Hadoop there are different scheduling algorithms are being used to scheduling jobs for FIFO algorithm the mechanism are being used is First In First Out compare to Fair algorithm to scheduling jobs the mechanism is hierarchical queue, in other hand , Capacity algorithm used queue to scheduling jobs.

The technique of scheduling algorithm we can summarized in the following:

1-queue mechanism?

2-pool mechanism?

3- Speculative Execution

4- Slot filtering and dynamic free slot advertisement

According to the result that has been done form our study we can conclude there is a lot of scheduling mechanism in big data in specific in Apache Hadoop.

The Table 5.2 can showing the result of all scheduling different type of scheduling mechanisms and which one dominantly used

Table 5:2 Scheduling mechanisms used in different type of algorithms

Mechanism	FIFO	Fair	Capacity	LATE	SAMR	Hybrid	Maestro	Delay	Dynamic	Deadline	Enhanced	Machmaking	Energy	Resource	Context	COSHH
Queue	×		×			×	×	×	×	×		×			×	×
Pool		×														
Slot filtering and dynamic free slot advertisement														×		
Speculative Execution				×	×						×			×		

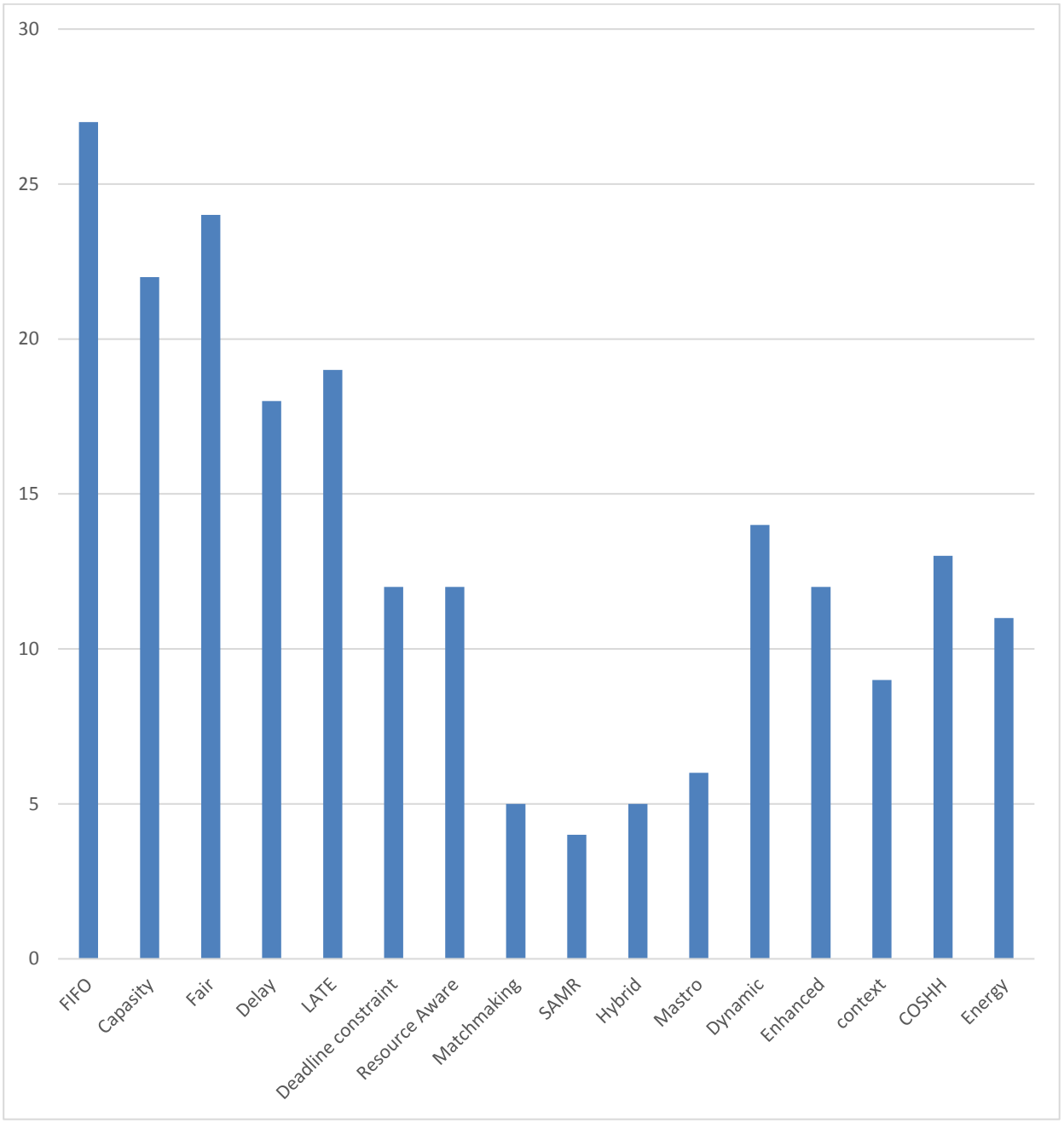

Figure 5.1: The most scheduling are being studied in literatures

RQ3: What are the main advantages and disadvantages of different schedulers on Big Data frameworks?

Scheduling play an essential part in Hadoop, where it used to reduce the time and improve the product of the processing. For that there a lot of advantages and disadvantages for each scheduler algorithm are being used in Hadoop or any other frameworks. The scheduler algorithms designed to work in a different type of workload and in a several environment. These advantages it fully discussed in Chapter 4 for each scheduling algorithms individually, here we just summarized the most cases that could be similar in a same type of algorithm. The most case of advantages are Simple of implement, poor locality, less complicity, decrease the execution time and improve performance. On the other hand, the disadvantages are Single type of job, complicity, wasted time and not-preemptive

Table 5.3: Advantages and Disadvantages cases for algorithms

Environment	cases	FIFO	Fair	Capacity	LATE	SAMR	Hybrid	Maestro	Delay	Dynamic	Deadline	Enhanced	Matchmaking	Energy	Resource	Context	COSHH
Advantages	Simple to implement	×					×		×	×			×				
	Poor Locality	×															
	Less complex	×				×	×		×								
	Decrease the execution time		×			×					×	×					
	Improve performance	×			×	×					×	×		×	×		×
Disadvantages	Single type of job		×									×					

	Comple x			×													
	Wasted time						×						×				
	Not preemp tive	×		×													

RQ4: What type of scheduling optimizations offered in literature?

Big data there are a lot of optimization was done it can be the backbone of the big data scheduling algorithms and processing huge data some of these make a new genuine algorithm and other make development and try to fill cons the algorithms already have, wherein these scheduler algorithms namely as following :

1. Fair scheduling Algorithm
2. Capacity Scheduling algorithm
3. Delay scheduling algorithm
4. Context aware scheduling algorithm
5. Deadline Constraint Scheduling Algorithm
6. Matchmaking Scheduling Algorithm
7. Enhanced Self Adaptive MapReduce Scheduling Algorithm
8. Self-Adaptive Reduce Scheduling Algorithm
9. COSHH Scheduling Algorithm
10. Longest Approximate Time to End (LATE)
11. Resource Aware Scheduling
12. Maestro Scheduling Algorithm
13. Hybrid Scheduling Algorithm

14. Energy Aware Scheduling
15. Dynamic Priority Scheduling

5.2 FUTURE DIRECTIONS

1. Making an experimental study on different type of scheduling in Apache Hadoop.
2. Try to probe one which challenges that make and effect on scheduling job
3. Increasing the number of scheduling algorithms used in comparison

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