



PROJECT NO. 50  
NKR: ON TOP SCHEDULER FOR APACHE MESOS

MS.PASINEE SANTIVORRANANT  
MR.SUPAPAT SRI-ON  
MS.PARATTHA WEERAPONG

A PROJECT SUBMITTED IN PARTIAL FULFILLMENT  
OF THE REQUIREMENTS FOR  
THE DEGREE OF BACHELOR OF ENGINEERING (COMPUTER ENGINEERING)  
FACULTY OF ENGINEERING  
KING MONGKUT'S UNIVERSITY OF TECHNOLOGY THONBURI  
2020

Project No. 50  
NKR: On top scheduler for Apache Mesos

Ms.Pasinee Santivorrnanant  
Mr.Supapat Sri-on  
Ms.Parattha Weerapong

A Project Submitted in Partial Fulfillment  
of the Requirements for  
the Degree of Bachelor of Engineering (Computer Engineering)  
Faculty of Engineering  
King Mongkut's University of Technology Thonburi  
2020

Project Committee

..... (Asst Prof.Rajchawit Sarochawikasit)	Project Advisor
..... (Asst Prof. Dr. Khajonpong Akkarajitsakul)	Committee Member
..... (Asst Prof. Dr. Phond Phunchongharn)	Committee Member
..... (Asst Prof. Sanan Srakaew)	Committee Member

Copyright reserved

Project Title	Project No. 50 NKR: On top scheduler for Apache Mesos
Credits	3
Member(s)	Ms.Pasinee Santivorrnanant Mr.Supapat Sri-on Ms.Parattha Weerapong
Project Advisor	Asst Prof.Rajchawit Sarochawikasil
Program	Bachelor of Engineering
Field of Study	Computer Engineering
Department	Computer Engineering
Faculty	Engineering
Academic Year	2020

### Abstract

The use of Big Data is becoming common these days by many companies. Large computers cluster is required to process Big Data instead of a single machine. Apache Mesos is a middleware that is used in datacenter to manage distributed computer clusters. It ensures that hardware resources are managed and shared fairly among multiple applications. However, Apache Mesos use Dominant Resource Fairness (DRF) that consider only dominant shared which can cause fairness-imbalance and failed tasks. For this reason, NKR: On top scheduler was developed for Apache Mesos. It considers both dominant shared and demand awareness to reduce the number of failed tasks and improve fairness. NKR-scheduler consists of 3 policies that are First Demand Policy (FDP), Success Rate Prediction and Hybrid Policy. For experiment, there are four tests run with three frameworks. The first test runs without NKR-scheduler. the other tests run with FDP, Success Rate Prediction and Hybrid Policy respectively. The result after applied NKR-scheduler with Apache Mesos can improve fairness and reduce failure rate.

**Keywords:** Apache Mesos / Scheduling / Dominant Resource Fairness / Multi-tenant / Fault tolerant / Artificial Intelligence

หัวข้อปริญญานิพนธ์	กลุ่มที่ 50 NKR: ตัวช่วยจัดการตารางงานสำหรับ Apache Mesos
หน่วยกิต	3
ผู้เขียน	นางสาวภาสินี สันติวรนนท์ นายศุภพัฒน์ ศรีอ่อน นางสาวปรีชญา วีระพงษ์
อาจารย์ที่ปรึกษา	ผศ.ราชวิชช์ สโรชวิสถิต
หลักสูตร	วิศวกรรมศาสตรบัณฑิต
สาขาวิชา	วิศวกรรมคอมพิวเตอร์
ภาควิชา	วิศวกรรมคอมพิวเตอร์
คณะ	วิศวกรรมศาสตร์
ปีการศึกษา	2563

#### บทคัดย่อ

ในปัจจุบัน Big Data เป็นสิ่งที่กำลังถูกใช้งานอย่างกว้างขวางในภาคธุรกิจและต้องการใช้เครื่องคอมพิวเตอร์หลายเครื่องในการประมวลผลข้อมูล เนื่องจากคอมพิวเตอร์เพียงเครื่องเดียวไม่เพียงพอสำหรับการประมวลผล ซึ่ง Apache Mesos เป็นเครื่องมือที่จะช่วยในการทำงานกับข้อมูลที่กระจายกันอยู่ในคอมพิวเตอร์หลายๆเครื่อง เพื่อกำหนดว่าแต่ละโปรแกรมจะสามารถเข้าถึงทรัพยากรได้อย่างเท่าเทียม อย่างไรก็ตาม Apache Mesos ใช้อัลกอริทึม Dominant Resource Fairness (DRF) ในการจัดสรรทรัพยากร แต่ว่า DRF นั้นจะพิจารณาเพียงแค่ทรัพยากรที่กำลังถูกใช้อยู่ในระบบ ทำให้การทำงานไม่สำเร็จ หรือทำให้ไม่ได้รับทรัพยากรในการทำงานอย่างเท่าเทียม ผู้จัดทำจึงได้สร้าง NKR-scheduler ซึ่งจะพิจารณาทั้งทรัพยากรที่กำลังถูกใช้อยู่ในระบบ และความต้องการใช้งานทรัพยากรของงานที่จะเข้ามาใหม่ เพื่อเพิ่มโอกาสสำเร็จและความเท่าเทียมในการเข้าถึงทรัพยากรให้กับระบบ ซึ่งภายใน NKR-scheduler ประกอบไปด้วย 3 หลักการ คือ First Demand Policy (FDP), Success Rate Prediction และ Hybrid Policy ในการทดลองได้มีการทดสอบผลลัพธ์ทั้งหมด 4 ครั้ง ประกอบไปด้วยการทดสอบโดยไม่ใช้ NKR-scheduler และทดสอบโดยใช้แต่ละหลักการตามลำดับ ผลลัพธ์จากการนำ NKR-scheduler มาใช้งานร่วมกับ Apache Mesos สามารถเพิ่มความเท่าเทียมของการเข้าถึงทรัพยากรและลดโอกาสความไม่สำเร็จของงานได้

**คำสำคัญ:** Apache Mesos / Scheduling / Dominant Resource Fairness / Multi-tenant / Fault tolerant / Artificial Intelligence

## **ACKNOWLEDGMENTS**

We could not complete this project without Asst. Prof. Rajchawit Sarochawikasit, an advisor of our project, for helping and supporting us to accomplish it smoothly. He shared his time to guide us from the beginning about how to do a research and he also helped us check about the format and the grammar in the report writing. We learned a lot from him and very pleased to thank him. We also would like to thank our committee for suggesting and giving some comments for us, without their comments we would not find the other views to evaluate and improve this project.

# CONTENTS

	<b>PAGE</b>
ABSTRACT	<b>ii</b>
THAI ABSTRACT	<b>iii</b>
ACKNOWLEDGMENTS	<b>iv</b>
CONTENTS	<b>vi</b>
LIST OF TABLES	<b>vii</b>
LIST OF FIGURES	<b>viii</b>
LIST OF SYMBOLS	<b>ix</b>
LIST OF TECHNICAL VOCABULARY AND ABBREVIATIONS	<b>x</b>
<b>CHAPTER</b>	
<b>1. INTRODUCTION</b>	<b>1</b>
1.1 Problem Statement and Approach	1
1.2 Objectives	1
1.3 Scope	1
1.4 Tasks and Schedule	2
<b>2. BACKGROUND KNOWLEDGE AND LITERATURE REVIEW</b>	<b>4</b>
2.1 Knowledge Background	4
2.2 Theoretical and Core Concepts	4
2.2.1 Tasks Failures Detection	4
2.2.2 Container Technology	5
2.2.3 Overview of Machine Learning	6
2.2.4 AI - Artificial Neural network	6
2.2.5 Deep Learning	6
2.3 Technologies survey	7
2.3.1 Apache Mesos	7
2.3.2 Zookeeper	8
2.3.3 Elasticsearch	8
2.3.4 Chronos	9
2.3.5 Marathon	9
2.3.6 Spark	10
2.3.7 Apache Kafka	11
2.4 Related Research	11
<b>3. METHODOLOGY AND DESIGN</b>	<b>13</b>
3.1 Project Functionality	13
3.1.1 Sequence diagram	13
3.1.2 Hypothesis Testing	14
3.2 System Architecture	15
3.2.1 Architecture diagram	15
3.2.2 Policy	16
3.2.3 Database Schema	18
3.3 Data management	19
3.3.1 Training dataset	19
3.3.2 Data pipeline	20
<b>4. EXPERIMENTAL SETUP AND RESULTS</b>	<b>21</b>
4.1 Setup cluster, framework application, and parameter	21

4.2	Model for predict success rate	23
4.2.1	Clustering	23
4.2.2	Random forest model	25
4.3	Policy 1: First Demand Share Policy (FDP)	25
4.4	Policy 2: Success Rate Prediction	28
4.5	Policy 3: Hybrid Policy	31
4.6	Summary of Result	35
<b>5.</b>	<b>CONCLUSIONS</b>	<b>36</b>
5.1	Result and Discussion	36
5.2	Conclusion	36
5.3	Future work	37
	<b>REFERENCES</b>	<b>38</b>

## LIST OF TABLES

TABLE	PAGE
1.1 Semester 1's Gantt chart	2
1.2 Semester 2's Gantt chart	3
2.1 Example of running 2 frameworks.	8
3.1 Variable description.	14
3.2 Variable description.	14
3.3 Parameter Formula and Description.	14
3.4 Description of Architecture diagram.	15
3.5 Parameter Formula and Description.	17
3.6 Decision Matrix.	17
3.7 Field name and description.	19
3.8 Framework of Apache Mesos.	19
3.9 Application Data.	20
4.1 Simulated task configuration.	21
4.2 Result from random forest model.	25
4.3 Average of CPU and memory utilization before and after using FDP.	27
4.4 Average of CPU and memory utilization before and after using Success Rate Prediction.	29
4.5 Average of CPU and memory utilization before and after using both FDP and success rate prediction.	33
4.6 Result of all metrics from Apache Mesos with and without apply each policy of NKR-scheduler.	35



## LIST OF FIGURES

FIGURE	PAGE
2.1 TaskTracker Failure Detection Model in Hadoop Framework	5
2.2 Virtual machine vs Container	5
2.3 Neural networks.	6
2.4 The Mesos architecture consists of one or more masters, slaves, and frameworks.	7
2.5 Mesos and Chronos provide a dynamic and fault-tolerant environment to run time-based jobs.	9
2.6 Mesos managing cluster resources for two applications.	10
2.7 Overview of Kafka.	11
3.1 Sequence diagram of Apache Mesos	13
3.2 Architecture diagram.	15
3.3 Architecture diagram.	16
3.4 Flow Diagram of Predicting success rate.	17
3.5 database schema.	18
3.6 Data pipeline.	20
4.1 Resources of the cluster	21
4.2 Number of tasks for each framework	22
4.3 Example of cluster metric data	22
4.4 Elbow method for optimal k	23
4.5 Data clustering visualize by CPU and memory utilization	23
4.6 Data clustering visualize by metrics that have high correlation	24
4.7 Data clustering visualize by metrics that have low correlation	24
4.8 Number of tasks for each framework after using FDP	25
4.9 Number of finished and failed tasks before and after using FDP	26
4.10 Growth rate of fail task before and after using FDP	26
4.11 CPU utilization before and after using FDP	27
4.12 Memory utilization before and after using FDP	27
4.13 System load before and after using FDP	28
4.14 Number of tasks for each framework after using Success Rate Prediction	29
4.15 Number of finished and failed tasks before and after using Success Rate Prediction	29
4.16 Growth rate of fail task before and after using Success Rate Prediction	30
4.17 CPU utilization before and after using Success Rate Prediction	30
4.18 Memory utilization before and after using Success Rate Prediction	31
4.19 System load before and after using Success Rate Prediction	31
4.20 Number of tasks for each framework after using Hybrid Policy	32
4.21 Number of finished and failed tasks before and after using Hybrid Policy	32
4.22 Growth rate of fail task before and after using Hybrid Policy	33
4.23 CPU utilization before and after using Hybrid Policy	33
4.24 Memory utilization before and after using Hybrid Policy	34
4.25 System load before and after using Success Rate Prediction	34

# LIST OF SYMBOLS

SYMBOL		UNIT
$m$	available types of resources	type
$n$	number of tasks on list	task
$r_j$	total resource of type $j$	unit
$rd_{i,j}$	resource demand of type $j$ being demand by framework $rd_i$	unit

## LIST OF TECHNICAL VOCABULARY AND ABBREVIATIONS

AI	=	artificial intelligence
API	=	Application Programming Interface
ANN	=	artificial neural network
AWS	=	Amazon Web Services
CPU	=	Central processing unit
DCOS	=	Datacenter Operating System
DD	=	Demand Dominant
DRF	=	Dominant Resource Fairness
DS	=	Demand Share
FDP	=	First Demand Policy
GB	=	GigaByte
I/O	=	Input and Output
IaaS	=	Infrastructure as a Service
MPI	=	Message Passing Interface
PaaS	=	Platform as a Service
RAM	=	random access memory

## CHAPTER 1 INTRODUCTION

This chapter will discuss the problem of Apache Mesos, the approach using in this project to solve the problem, the objectives and scopes to clarify what it does, and lastly tasks and schedule showing the overall processes to do it.

### 1.1 Problem Statement and Approach

At present several different types of applications are executed in clouds or large computer clusters. There are short or long time processing jobs, container orchestration, or MPI jobs. Multiple users can demand different resources to execute their tasks. Apache Mesos is a Middleware for the data center. It introduces an abstraction layer that provides an entire data center as a single large server. Instead of focusing on one application that running on a specific server, Apache Mesos resource-isolation allows multi-tenant (the ability to run multiple applications on a single machine). Default sharing of multiple resources in this multi-tenant environment is defined by the Dominant Resource Fairness (DRF) policy. Mesos frameworks receive the resources based on their current usage, which are responsible for scheduling their tasks within the allocation. In case of multiple schedulers, they can cause the fairness-imbalance in a multi-user environment. For example, greedy scheduler may consume more than its share of resources. Running multiple small tasks is better than launching large tasks in terms of waiting time of resource allocation.

Therefore, this project aims to improve the fairness of the scheduler by reducing the unfair waiting time due to higher resource demand in a pending task list and use log data to improve the whole cluster.

### 1.2 Objectives

- To study how jobs are scheduled in Apache Mesos
- To study how to develop an algorithm to improve performance of scheduler in large-scale clustered environments.
- To evaluate result and compare with Apache Mesos scheduler by using different job types in the list (short job, long job, MPI)

### 1.3 Scope

- This project focuses on the reduction of failed jobs.
- Design and develop an add-on architecture on top of the Apache Mesos scheduler, to track and distribute the incoming tasks.
- Find the limitations of existing approaches.





## CHAPTER 2 BACKGROUND KNOWLEDGE AND LITERATURE REVIEW

This chapter will discuss background knowledge about Apache Mesos. There are theoretical and core concepts that is important to understand this project such as, Tasks Failures Detection, Container Technology, Machine Learning, AI, and Deep Learning. The related technologies that might be used are Apache Mesos, Zookeeper, Elasticsearch, Chronos, Marathon, Spark, and Apache Kafka. Last topic is the related researches that explain how other researchers solve this kind of problem.

### 2.1 Knowledge Background

In 2009, Apache Mesos [6] was a research project at the University of California in Berkeley. Benjamin, et al. wanted to improve data center efficiency by allowing multiple applications to share a single computing cluster across several servers that make up a modern datacenter. So, multiple applications can share the processor, memory, and hard drive with any laptop or workstation. In 2010, the Mesos project entered the Apache Incubator, an arm of the Apache Software Foundation, so this project can gain the full support of the ASF's efforts. In 2013, The Apache Mesos project graduated from the incubator and founded Mesosphere. Mesosphere's flagship product, the Datacenter Operating System (DCOS), commercializes the open-source project by providing a turnkey solution to enterprises looking to deploy applications and scale infrastructure as effortlessly as other companies using Mesos, such as Airbnb, Apple, and Netflix.

Most operating systems only fairly divide and account for CPU cycles. So, performance isolation is essential to operating systems shared by dependable services. These dependable services require specifying and enforcing policies for all resources, and that current metrics for evaluating fair sharing are insufficient. In 2006, Aage Kvalnes et al. researched new policy specifications and metrics, and illustrated these with the help of a new operating system that supports holistic resource sharing. [17]

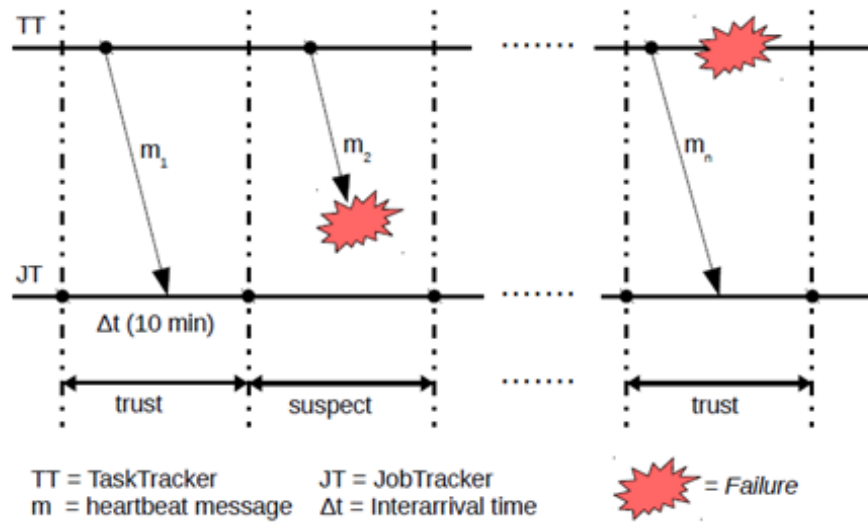
In data centers and clouds, where applications could be co-scheduled on the same physical nodes, resource fairness needs to extend to multiple resource types such as memory, disk I/O, and network bandwidth. Ali, et al. considered the problem of fair resource allocation in a system containing different resource types, where each user may have different demands for each resource and researched about a new generalization of max-min fairness to multiple resource types called Dominant Resource Fairness (DRF). [5]

### 2.2 Theoretical and Core Concepts

#### 2.2.1 Tasks Failures Detection

Hadoop usually uses JobTracker to detect failures of the TaskTracker nodes. It detects with heartbeat-based failure detection. The TaskTracker will send heartbeat message to JobTracker and JobTracker will declare a TaskTracker as dead only when it does not receive heartbeat for a limited time. It cannot quickly detect the failures and it may assign task to dead nodes. This can increase the number of failure tasks in Hadoop. [15]

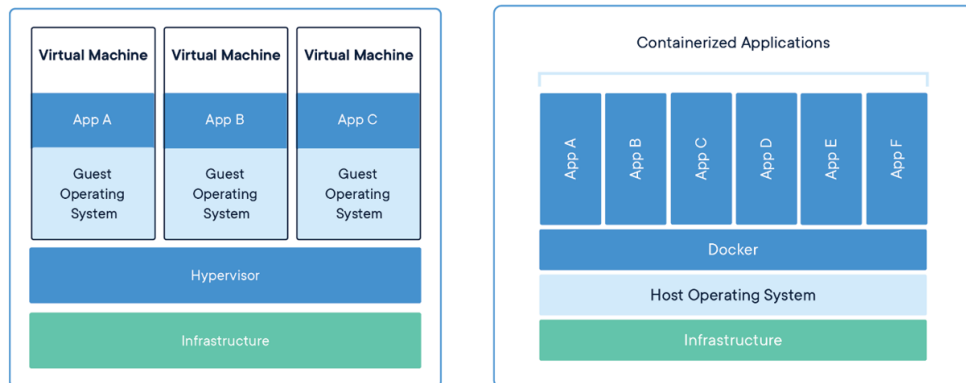
For example, active TaskTracker send heartbeat messages to JobTracker every 3 seconds. While JobTracker check the timeout condition every 200 seconds. If network delays or messages losses, some heartbeat may arrive late or loss. The JobTracker may consider that TaskTracker as dead node even it is available as shown in **Figure 2.1**. that heartbeat message m2 does not arrive and the JobTracker consider this TaskTracker as dead.



**Figure 2.1** TaskTracker Failure Detection Model in Hadoop Framework

[From: Adaptive Failure-Aware Scheduling for Hadoop. (Mbarka Soualhia, Montreal, Quebec, Canada, 2018)]

## 2.2.2 Container Technology



**Figure 2.2** Virtual machine vs Container

[From: Docker, "What is a Container?," [Online]. Available: [www.docker.com/resources/what-container](http://www.docker.com/resources/what-container). Accessed 30 August 2020]

Container Technology is a method to package up code and all its dependencies, so the application runs quickly and reliably from one computing environment to another, with container software having names including the popular choices of Docker, Apache Mesos, RKT, and Kubernetes. The virtual machine contains the entire operating system. Therefore, the physical server that runs several virtual machines is running several operating systems' simultaneously as shown in **Figure 2.2**. [2]

There is a lot of overhead on virtual machine. In contrast, with container technology, the server runs a single operating system. Each container can share this single operating system with other containers on server. Containers require less resource of server with less overhead and more efficient than virtual machines. [1] Containers are set up to accomplish work in a multiple container architecture (container cluster). They also enable a program to be broken down into smaller pieces, which are known as microservices. So, the program can work on each of the containers separately.



### 2.2.3 Overview of Machine Learning

Machine Learning is a branch of artificial intelligence (AI). It is the machine's ability to learn from data provided without human intervention and able to improve decision from experience. Without human directed programming instructions, the machine accesses data, observes and finds data pattern. The more data input the better data pattern learning and better decision making.[3]

### 2.2.4 AI - Artificial Neural network

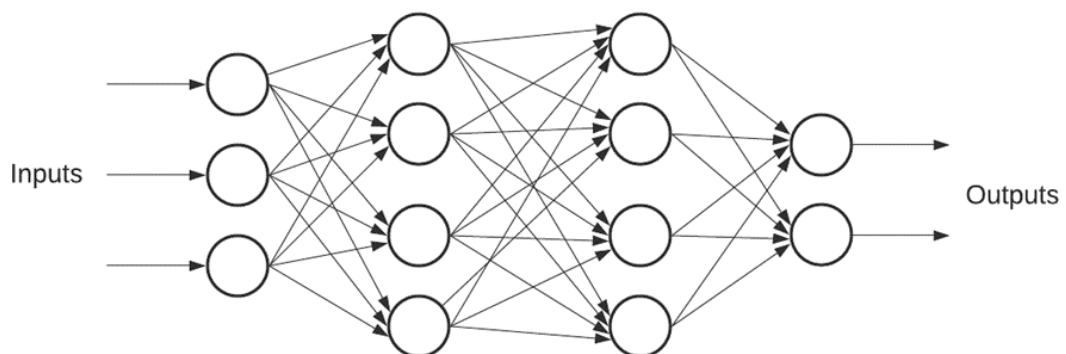
An artificial neural network (ANN) is a computational model imitates the natural human brain. The network consists of hundreds or thousands small neuron nodes. Those numerous neuron nodes communicate to each other in the web form. The neuron node is called processing unit. Each of processing unit is interconnected by nodes. Each processing unit comprises of input unit and output unit. Input unit receives various type of data format. It also has an internal weighting system. The neural network learns from the input and produce output result.

ANN use rules and guidelines to generate result/ output. The set of these learning rules is called backpropagation because it uses backward propagation of error to learn or improve the better result. ANN learns data patterns in training phase. It compares actual output with the desired output that is expected result in supervised phase. The difference between actual and expected result are worked backward to adjust the weight of its connections between the units. The purpose is to make the lowest possible error. [4]

### 2.2.5 Deep Learning

Nowadays, there are collections of vast unlabeled and unstructured data gathering from various sources that is difficult to analyses useful information by traditional programs in a linear way. The hierarchical level of artificial neural network that work in web form to process data with a nonlinear approach is called Deep Learning. The first layer of the neural network processes a raw data and pass output on to the next layer. The second layer processes first layer output plus additional information and pass output to next layer again. This continues across all levels of the neuron network to make information more meaningful information. [12]

Deep learning models can achieve high accuracy, sometimes exceeding human-level performance. "Deep" refers to the powerful number of hidden layers in the neural network. However, it needs lots of labeled data and high-performance machines to analyze. The organized layers of interconnected nodes can be tens or hundreds of hidden layers. [16] as shown in **Figure 2.3**.

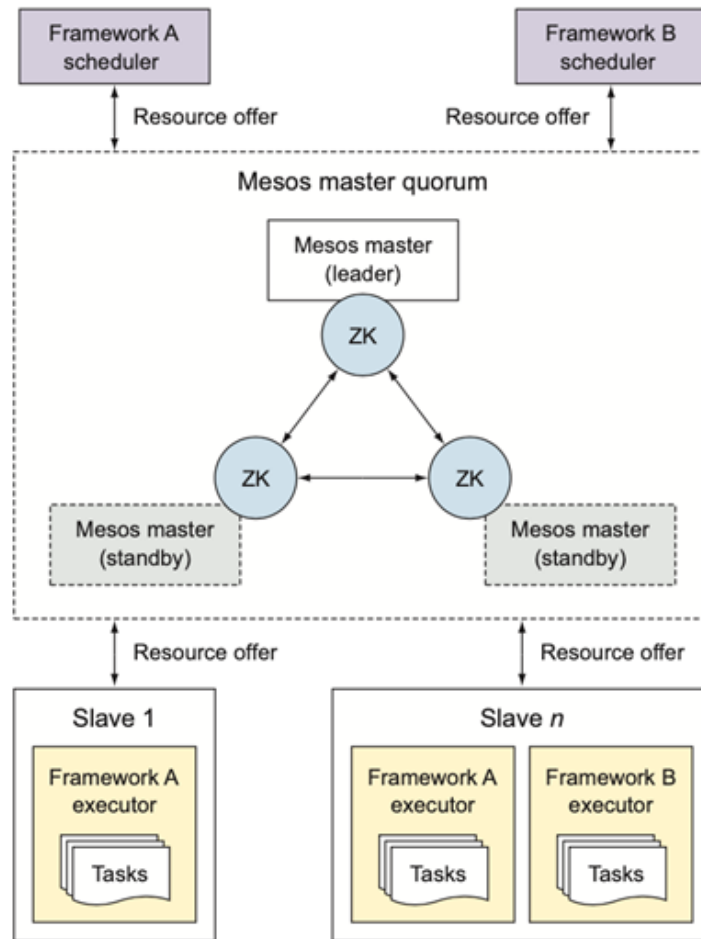


**Figure 2.3** Neural networks.

## 2.3 Technologies survey

### 2.3.1 Apache Mesos

Mesos consists of a master, agent daemons running on each cluster node, and Mesos frameworks that run tasks on these agents as shown in **Figure 2.4**. Architecture consists of three components: masters, slaves, and the frameworks that run on them. Mesos relies on Apache ZooKeeper, a distributed database used specifically for coordinating leader election within the cluster, and for leader detection by other Mesos masters, slaves, and frameworks. [8]



**Figure 2.4** The Mesos architecture consists of one or more masters, slaves, and frameworks.

[From: Ignazio, R. Mesos in Action (Manning Publications Co., Shelter Island, NY, 2016).]

1. **Masters:** Mesos masters are responsible for managing the Mesos slave daemons running on each machine in the cluster. Using Zookeeper, they coordinate which node will be the leading master, and which masters will be on standby, and ready to take over if the leading master goes offline. A Mesos cluster requires minimum one master, and three or more are recommended for production deployments. Zookeeper can run on the same machines as the Mesos masters themselves or use a standalone Zookeeper cluster.
2. **Slaves:** The machines in a cluster are responsible for executing a framework's tasks.

3. **Frameworks:** Mesos application that is responsible for scheduling and executing tasks on a cluster. A framework is made up of two components: a scheduler and an executor.

- **Schedulers** A scheduler is a long-running service responsible for connecting to a Mesos master and accepting or rejecting resource offers. Mesos delegates the responsibility of scheduling to the framework, instead of attempting to schedule all the work for a cluster itself. The scheduler can then accept or reject a resource offer based on whether it has any tasks to run at the time of the offer.
- **Executor** An executor is a process launched on a Mesos slave that runs a framework's tasks on a slave.

Dominant resource is a resource of specific type (CPU, memory, disk, ports) which is most demanded by given framework among other resources it needs. DRF computes the share of resources allocated to a framework (dominant share) and tries to maximize the smallest dominant share in the system for next round offers the resources first to the one with smallest dominant share, then to the second smallest one and so on. [9] Example with 9 CPUs and 18 GB RAM to two frameworks running task that require <1 CPU, 4GB> and <3CPUs, 1GB> shown in **Table 2.1**.

**Table 2.1** Example of running 2 frameworks.

Schedule	Framework A		Framework B		total	
	Resource Share	Dominant Share	Resource Share	Dominant Share	CPU	RAM
B	<0, 0>	0	<3/9, 1/18>	1/3	3/9	1/18
A	<1/9>, <4/18>	<b>2/9</b>	<3/9, 1/18>	1/3	4/9	5/18
A	<2/9>, <8/18>	4/9	<3/9>, <1/18>	<b>1/3</b>	5/9	8/18
B	<2/9>, <8/18>	<b>4/9</b>	<6/9>, 2/18>	2/3	8/9	10/18
A	<3/9>, <12/18>	2/3	<6/9>, 2/18>	2/3	1	14/18

### 2.3.2 Zookeeper

ZooKeeper is an open-source Apache project that provides a centralized service for providing configuration information, naming, synchronization, and group services over large clusters in distributed systems. The goal is to make these systems easier to manage with improved and more reliable propagation of changes. ZooKeeper provides an infrastructure for cross-node synchronization by maintaining status type information in memory on ZooKeeper servers. A ZooKeeper server keeps a copy of the state of the entire system and persists this information in local log files. Large Hadoop clusters are supported by multiple ZooKeeper servers, with a master server synchronizing the top-level servers. [7]

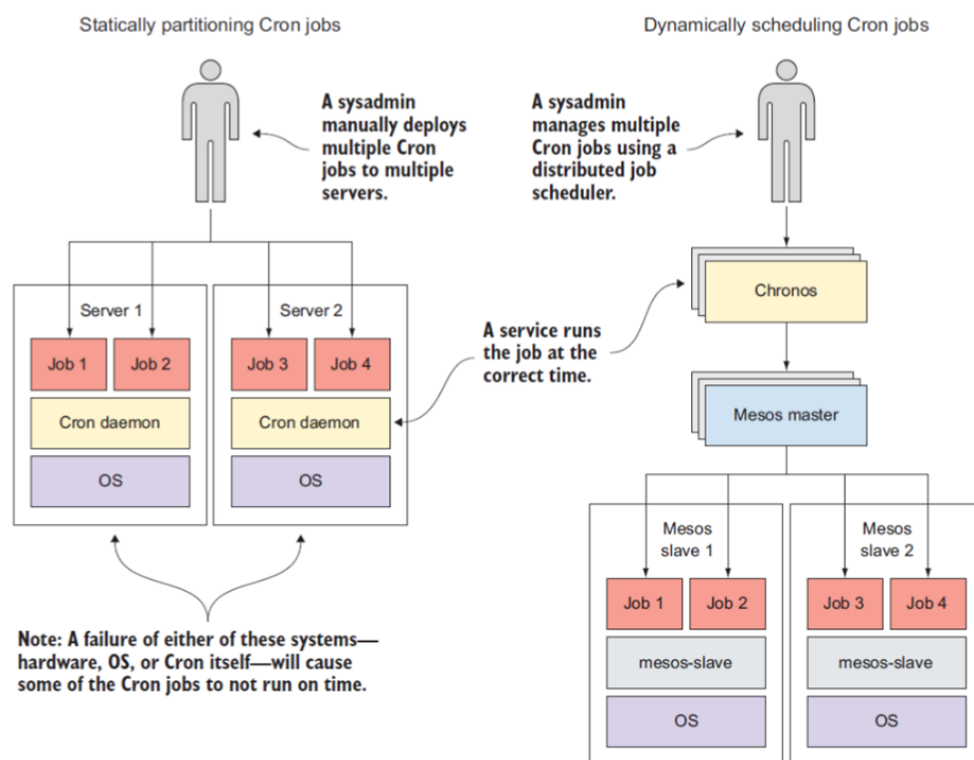
### 2.3.3 Elasticsearch

Elasticsearch is an open-source search and analytics engine built on Apache Lucene and developed in Java. Elasticsearch can be used to store and search all kinds of documents, analyze huge volumes of data in near real-time and give back answers in milliseconds, and supports multitenancy. It's able to achieve fast search responses because it searches an index directly instead of searching the text. Related data is often stored in the same index, which consists of one or more primary shards, and zero or more replica shards. Once an index has been created, the number of primary shards cannot be changed. It uses a structure based on documents and comes with extensive REST APIs for storing and searching the data.

Elasticsearch is the component of the Elastic Stack. Elastic Stack is a set of open-source tools for storage, analysis, and visualization. The four components are Elasticsearch, Logstash, Kibana and Beats. They are designed for use as an integrated solution. It is commonly referred to as the “ELK” stack.[13]

### 2.3.4 Chronos

Chronos is the Mesos Cron system. It handles time-based scheduling of jobs on a Mesos cluster. Chronos can be used to schedule commands or scripts. The Chronos feature set is easily and reliably to create standalone schedule-based jobs, as well as complex dependency-based jobs and pipelines, simply by specifying the schedule and resources that the job requires. This guarantees that time-based jobs are running on time while continuing to use datacenter resources as efficiently as possible. In **Figure 2.5**, it shows about the differences between running Cron jobs on a single machine and running them on a Mesos cluster.[8]



**Figure 2.5** Mesos and Chronos provide a dynamic and fault-tolerant environment to run time-based jobs.

[From: Ignazio, R. Mesos in Action (Manning Publications Co., Shelter Island, NY, 2016).]

### 2.3.5 Marathon

Marathon is a popular open source Mesos framework developed by Mesosphere. Marathon is used for deploying long-running services and applications, both in Linux cgroups and Docker containers. It can also be considered a private platform as a service (PaaS) on which to deploy applications. Marathon can specify the resources needed for each instance of an application and number of running instances. If a Mesos slave fails, or an instance of application crashes or exits, Marathon will automatically start a new instance to replace the failed one.

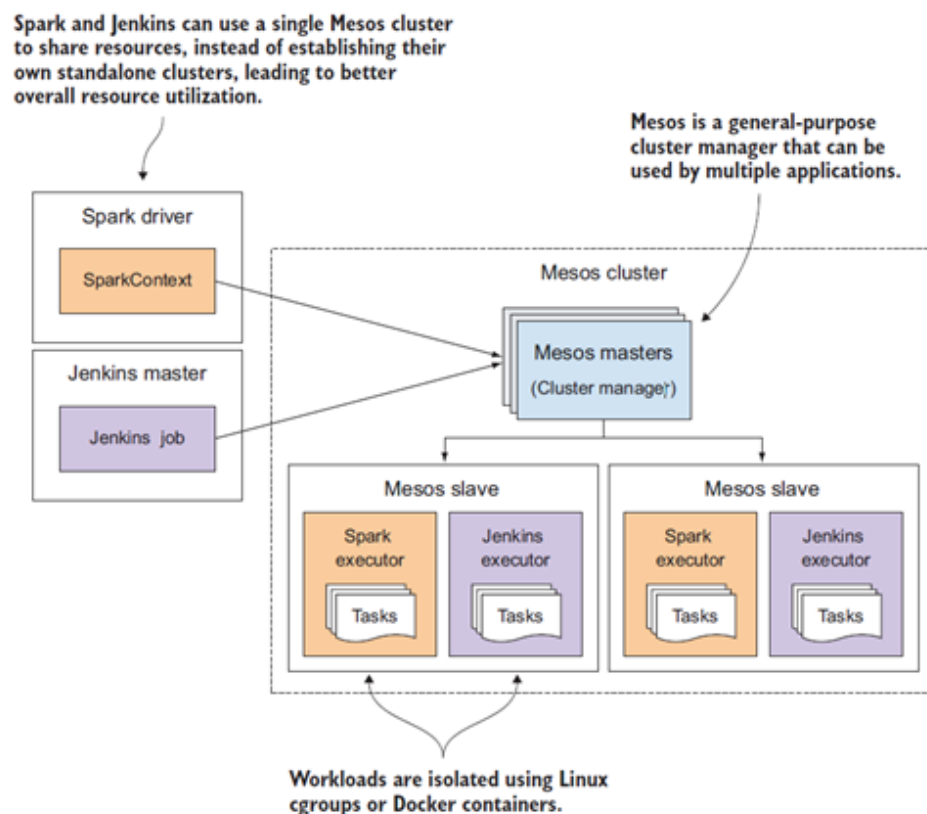
Marathon also allows users to specify dependencies on other services and applications during deployment, so an application instance cannot start before its database instance is up and passing health checks. Marathon contains a list of features that should satisfy the needs of most application management scenarios

such as managing applications and groups of applications with dependencies and health checks, rolling application upgrades with specific capacity requirements, a powerful web interface and REST API, and high availability (using ZooKeeper for leader election and coordination).[8]

### 2.3.6 Spark

Apache Spark is unified analytics engine for large-scale data processing. It runs on Hadoop, Apache Mesos, Kubernetes, standalone, or in the cloud. It can access diverse data sources. Spark perform task faster and more efficiently than Hadoop's MapReduce, both in memory and on disk in many cases. Spark also provide API for several programming language, including Python, Scala, and Java and support streaming workloads, interactive queries and machine learning libraries, in addition to MapReduce-like batch processing. Spark can run locally. But that is useful only for development purpose, the number of CPU cores limits the number of executors. When setting up a production Spark cluster, there are two option.

When setting up statically partitioned cluster on an Infrastructure as a Service (IaaS) provider. It will be wasting money due to cloud instances sitting idle. Find-grained resource sharing can help increase system's utilization. For example, if there are two applications likes in **Figure 2.6**, Spark and Jenkins that need to run on multiple servers. Each of these system atop a general-purpose cluster manager like Mesos that allows for this sort of fine-grained resource sharing. It can share compute resources and run multiple workloads on a single Mesos slave. This will lead to better resource utilization across many machines within a modern datacenter.[8]

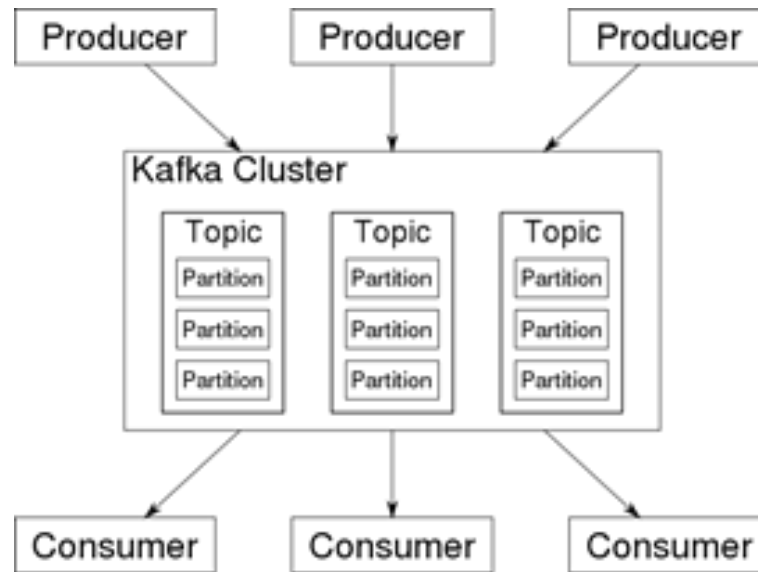


**Figure 2.6** Mesos managing cluster resources for two applications.

[From: Ignazio, R. Mesos in Action (Manning Publications Co., Shelter Island, NY, 2016).]

### 2.3.7 Apache Kafka

Apache Kafka is an open-source stream-processing software platform. Apache Kafka is providing a unified, high-throughput, and low-latency platform for handling real-time data feeds. Kafka allows user to subscribe itself and publish data to any number of systems or real-time applications. In **Figure 2.7**, producers are processes that send message to Kafka. Kafka stores these messages in key-value. The data can be partitioned into different topic. Consumers are process that can read messages from partitions. Kafka runs on a cluster of one or more server, And the topics are distributed across the cluster nodes. Partitions are replicated to multiple servers.[18]



**Figure 2.7** Overview of Kafka.

[From: wikipedia."Kafka".[online].Available:[en.wikipedia.org/wiki/Apache\\_Kafka](https://en.wikipedia.org/wiki/Apache_Kafka).Accessed 25 November 2020]

## 2.4 Related Research

The current data center management is a representative large-scale resource management and scheduling framework for clusters, liked the open-source project Mesos [8]. However, the data center environment are cluster systems and variety of submitted tasks, such as Hadoop clusters that support Big Data processing and Spark clusters that support in-memory computing. Mesos is a resource allocation method with no differential task type and scheduler does not consider the overall resource demand or workload, which leads to low average resource utilization and starve were a framework with a high demand on queue. Moreover, Mesos uses the DRF (Dominant Resource Fairness) algorithm for resource allocation. The DRF algorithm is the default scheduling algorithm of Mesos, the algorithm still has the disadvantage of not considering the machine performance and task type.

Many researchers have conducted relevant work. For example, in 2016, Li Y et al [10] introduced the fish swarm intelligence algorithm to dynamically adjusting the Mesos cluster resources to improve the Mesos load imbalance and resource utilization. The DRF scheduling algorithm of Mesos is extended, and in 2018, Wenbin Liu et al. proposed A X-DRF algorithm [11] based on building classifies the performance of physical machines and job type judgment classification is proposed to solve the problem of machine performance in literature, but the task type is not considered and not consider the waiting time. Compared with the original DRF algorithm, the X-DRF algorithm has higher system resource utilization rate, which is in line with the

actual production rules of data centers, and provides new ideas for heterogeneous cluster multi- resource management for data center managers. In 2019, Pankaj Saha et al. developed Tromino [14], a policy driven queue manager. Tromino allows task from individual frameworks to be scheduled based on each framework's overall resources requirement and current resources consumption. Tromino reduce the impact of unfairness due to framework specific configuration and unfair waiting time due to higher resource demand in a pending task queue.

## CHAPTER 3 METHODOLOGY AND DESIGN

This chapter show how NKR-scheduler works with Apache Mesos. The NKR-scheduler consist of two policies, First Demand Policy and Success Rate Prediction. First Demand Policy consider both demands of each framework and dominant share from cluster to improve the fairness. Success Rate Prediction use log data to predict success rate of incoming task to reduce number of failed tasks. The hypothesis is proved by running three frameworks of Marathon, Chronos, and Spark with Normal Cluster Setting and NKR-scheduler. The evaluation metrics are fairness, number of failed tasks, CPU and memory utilization, system load, and running time.

### 3.1 Project Functionality

This project is based on the hypothesis if the dominant share and demand awareness is known by meta-scheduler, the failure job in each framework will be reduced. It aims to design additional architecture (meta-scheduler) of Apache Mesos to prove the hypothesis above. The user submits the task directly to the meta-scheduler. When the meta-scheduler accepts tasks, it aggregates all tasks based on data from cluster master for a better fairness and utilization.

#### 3.1.1 Sequence diagram

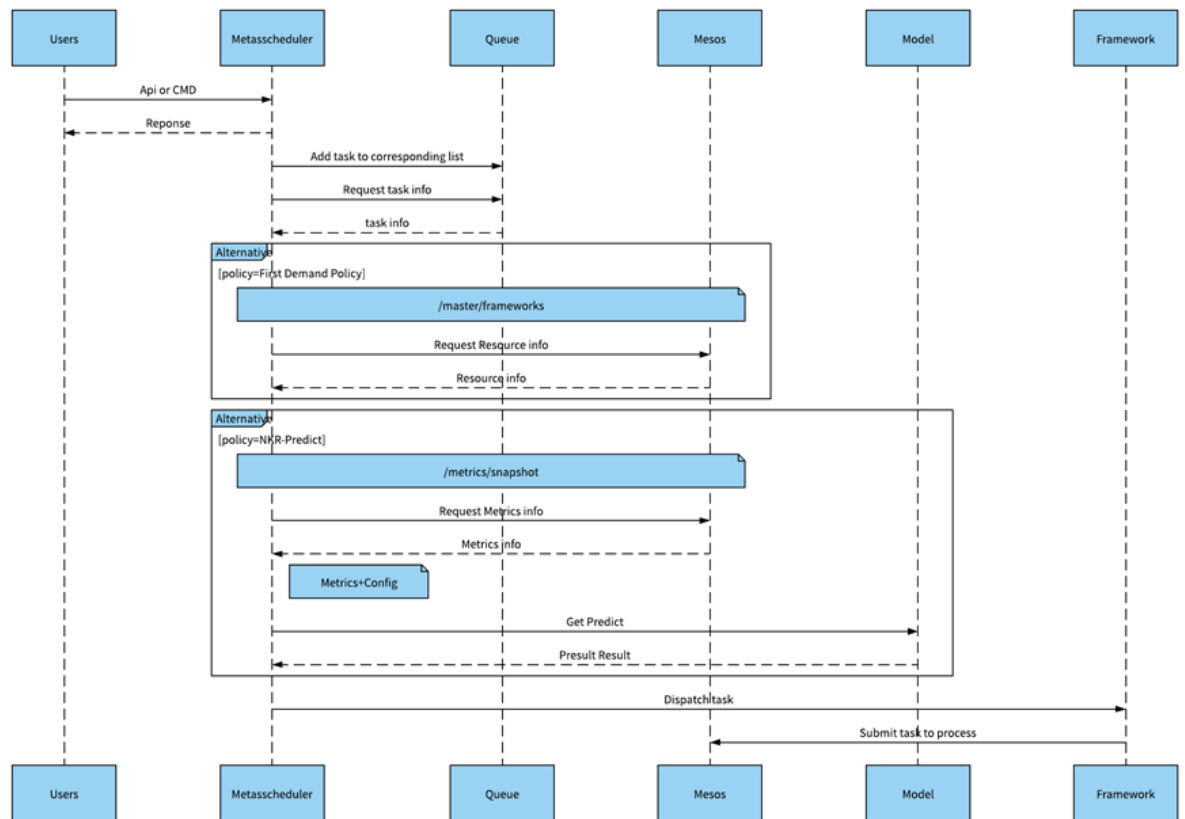


Figure 3.1 Sequence diagram of Apache Mesos

Figure 3.1 shows sequence diagram that user submits a job via command line or Application Programming Interface (API), and also specifies their framework, resources requirement, configuration script,



and command to the meta-scheduler. The meta-scheduler, called NKR-scheduler, keeps track of incoming task from user and distributes each task to the queue. NKR-scheduler periodically fetches cluster and task information from Mesos Master to make a decision for task scheduling based on pre-defined policy (to be explained in Topic 3.2.2). After NKR-scheduler finishes a decision-making process, it will dispatch task directly to corresponding framework.

### 3.1.2 Hypothesis Testing

Hypothesis Testing was set up in order to prove that NKR-scheduler can reduce number of failed task and improve fairness in each framework by considering both Dominant share and Demand awareness which describes more detail in **Table 3.1**. There are three frameworks which are Marathon, Chronos, and Spark for the test. The results were compared using four criteria for executing framework;

1. **Normal Cluster Setting:** not using NKR-scheduler
2. **NKR-scheduler:** apply with Policy 1 (First Demand Share Policy)
3. **NKR-scheduler:** apply with Policy 2 (Success Rate Prediction)
4. **NKR-scheduler:** apply with both Policies (Hybrid Policy)

**Table 3.1** Variable description.

Variable	Description
<b>Dominant share</b>	The resource that each framework uses in cluster at that point of time
<b>Demand awareness</b>	resource requirement of each framework

**Experiment:** Frameworks with same arrival rate and all tasks are vary in a resource consumption as shown in **Table 3.2**. This experiment will run 3 times consist of 1) First Demand Share Policy, 2) Success rate prediction, and 3) Hybrid Policy.

**Table 3.2** Variable description.

	Number os tasks	Arrival rate (sec)
<b>Marathon</b>	33	2
<b>Chronos</b>	33	2
<b>Spark</b>	33	2

The evaluation metrics are

1. **Improving of fairness:** It is evaluated by averaging different task number of each framework. The lower different number is the better fairness among frameworks. The formular to it is shown in **Table 3.3**

**Table 3.3** Parameter Formula and Description.

Formula	Description
$fairness = \frac{ t_m - t_c  +  t_m - t_s  +  t_c - t_s }{3}$	$t_m$ average number of Marathon task $t_c$ average number of Chronos task $t_s$ average number of Spark task

2. **Reduction of failed tasks:** It is evaluated by number of failed tasks.
3. **Additional:** CPU and memory utilization, number of processes were waiting for the CPU (system load), and running time of each frameworks.

## 3.2 System Architecture

### 3.2.1 Architecture diagram

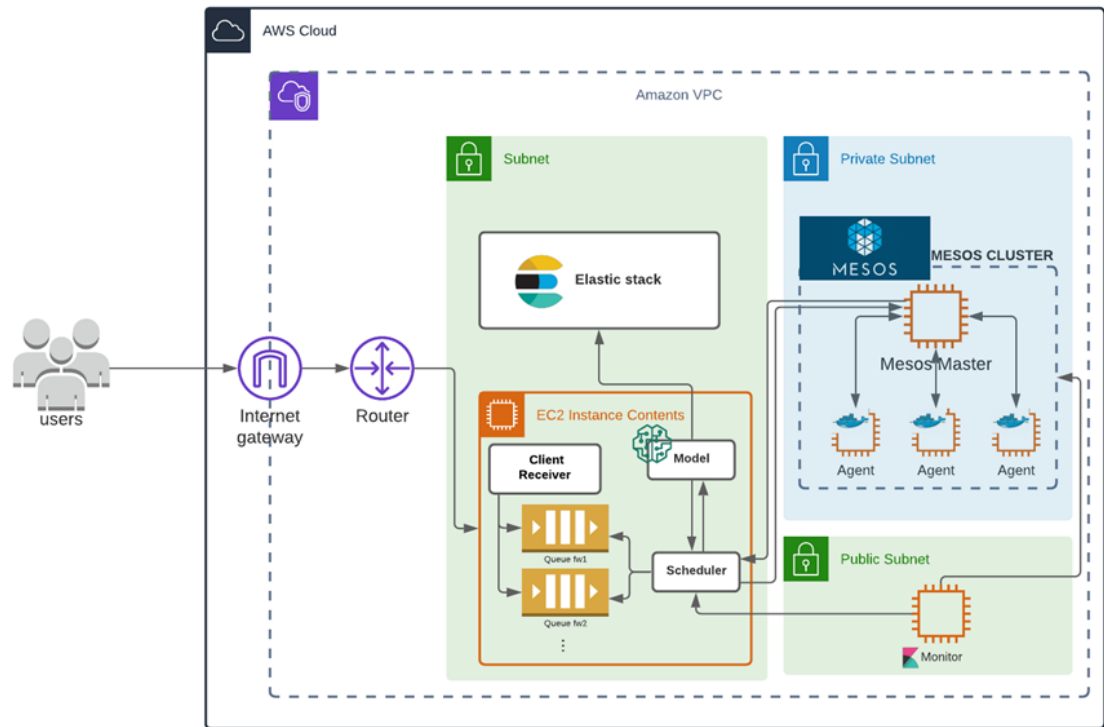


Figure 3.2 Architecture diagram.

According to **Figure 3.2** shows architecture diagram, there are many components that this project implements. NKR-scheduler consists of three major components 1) Client Receiver, 2) Queue, and 3) Scheduler and the other components describe below in **Table 3.4**.

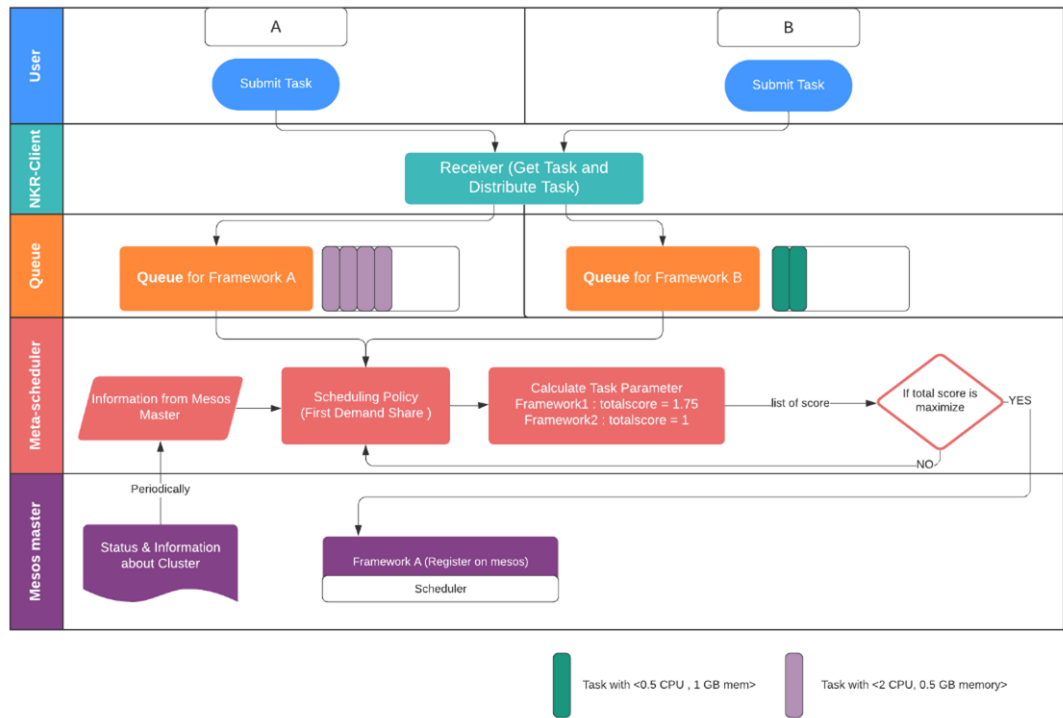
Table 3.4 Description of Architecture diagram.

Components	Description
<b>Client Receiver</b>	Interface for user to submit task to cluster.
<b>Queue</b>	The list that stores task and information about resources requirement in each framework that register into the Apache Mesos.
<b>Scheduler</b>	The adaptive policy that configured by user and keeps track information about cluster from Apache Mesos.
<b>Elasticsearch</b>	Elasticsearch stores previous data from Apache Mesos and periodically train a new model.
<b>Monitor</b>	Monitor keeps track abnormality and another metrics.
<b>Model</b>	It stores model for predicting in case user want to use AI to schedule tasks.

### 3.2.2 Policy

This project designs two policies for the Meta-scheduler: 1) First Demand Policy (FDP), and 2) Success rate prediction. These policies can be extended further based on scheduling needs of users.

1. **First Demand Share Policy** We explain how FDP policy work by considering, a cluster with a total of 8 CPU and 64 GB of memory, where two frameworks (A and B) are shared completely shared resources. Each framework can have different number of tasks in its list. In example, framework a has 4 tasks each task consumes (2 CPU, 0.5GB memory) as a resource demand, and Framework B has 2 tasks with (0.5 CPU, 1 GB memory) and task still running on cluster. Framework A has 1 task (2CPU, 0.5 GB memory), and Framework B has 2 task (1CPU, 2 GB memory) the dominants share of framework A =  $\max(2/8, 0.5/64) = 25\%$  and Framework B =  $12.5\%$ . In this case if we apply normal scheduling policy it will dispatch task from framework B as shows in **Figure 3.3**.



**Figure 3.3** Architecture diagram.

In FDP policy, we consider both the demands of each framework and their dominant share that come from cluster monitor. Scheduling only based on the demand may cause unfairness. A framework could end up consuming the entire cluster due to its higher demand while another framework that has significantly fewer number of tasks to execute could starve for resources. Therefore, we combine both as a factor and use decision matrix in each cycle to decide which task to be dispatched. We present how to calculate each parameter in **Table 3.5**. according to **Table 3.6**, We can see highly total factor in framework A, therefore program assign a higher priority and let its corresponding dispatcher release a task

**Table 3.5** Parameter Formula and Description.

Parameter name	Formula	Description
<b>Demand Dominant (DD)</b>	$DD_i = \max_{j=1}^m (\frac{n_i r_{d_{i,j}}}{r_j})$	$m$ available types of resources
		$n_i$ number of tasks on list $i$
		$r_{d_{i,j}}$ resource demand of type $j$ being demand by framework $rd_i$
		$r_j$ total resource of type $j$
<b>Dominant Share (DS)</b>	$DS_i = \max_{j=1}^m (\frac{n_i}{r_j})$	$m$ available types of resources
		$n_i$ number of tasks on list $i$
		$r_j$ total resource of type $j$

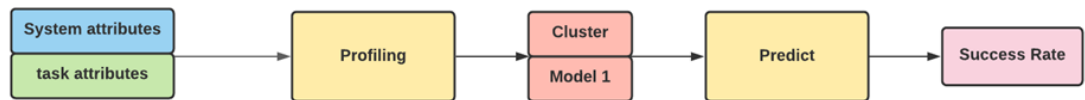
**Table 3.6** Decision Matrix.

Framework	DD	(1-DS)	TOTAL
<b>A</b>	1	0.75	1.75
<b>B</b>	0.125	0.875	1

2. **Success rate prediction** There are many metrics in this policy that affect system or task performance, such as CPU utilization, free memory, storage in use, message send information, message queue length, average execution time, etc. These metrics are able to identify anomalies (task failed, task killed, and etc.) by using the pipeline provided in **Topic 3.3.2**

Firstly, the log data need to be pre-processed by transforming and cleaning. Secondly, the log data are clustered by K-means algorithm to separate the data that point into different metric groups or different machines. The success rate prediction of given task will use the Random Forest. Random Forest is a set of interconnected decision tree that uses the majority voting to provide classification or regression result. It is robust to noise and able to provide highly accurate prediction. [15] In each cluster, the model will be trained by active and terminated tasks information.

In each cluster, data will be divided into 80% training dataset and remaining 20% testing dataset. The measure metric is accuracy, precision, recall, and error. When users submit task, NKR-scheduler will request metric information from Mesos, allocate resource to run tasks, profile the task to data cluster and use that cluster model to predict success rates of their task shown in **Figure 3.4**.

**Figure 3.4** Flow Diagram of Predicting success rate.

### 3.2.3 Database Schema

This project implement database as a Elasticsearch and keep log every minute. It allows storing, searching, and analyzing big volumes of data quickly and schema-less. It uses a default configuration to index the data. Database schema shows in **Figure 3.5** and describe each field in **Table 3.7**

Resources
master/cpus_used
master/cpus_total
master/disk_used
master/disk_total
master/mem_used
master/mem_total

System
system/load_15min
system/load_5min
system/load_1min

Slaves
master/slaves_active
master/slaves_connected

Tasks
master/tasks_error
master/tasks_failed
master/tasks_finished
master/tasks_killed
master/tasks_lost
master/tasks_running
master/tasks_staging
master/tasks_starting

Frameworks
master/frameworks_active
master/frameworks_connected
master/frameworks_disconnected
master/frameworks_inactive
master/outstanding_offers

Messages
master/invalid_framework_to_executor_messages
master/invalid_status_update_acknowledgements
master/invalid_status_updates
master/dropped_messages
master/messages_authenticate
master/messages_deactivate_framework
master/messages_exited_executor
master/messages_framework_to_executor
master/messages_kill_task
master/messages_launch_tasks
master/messages_reconcile_tasks
master/messages_register_framework
master/messages_register_slave
master/messages_reregister_framework
master/messages_reregister_slave
master/messages_resource_request
master/messages_revive_offers
master/messages_status_udpate
master/messages_status_update_acknowledgement
master/messages_unregister_framework
master/messages_unregister_slave
master/valid_framework_to_executor_messages
master/valid_status_update_acknowledgements
master/valid_status_updates

**Figure 3.5** database schema.

**Table 3.7** Field name and description.

Index Name	Description		
<b>Resources index</b>	The following metrics provide information about the total resources available in the cluster and their current usage.		
<b>System index</b>	The following metrics provide information about the resources available on this master node and their current usage.		
	Field name	Data type	Description
	Load_15min	Double	Load average for the past 15 minutes
	Load_5min	Double	Load average for the past 5 minutes
	Load_1min	Double	Load average for the past 1 minutes
<b>Slave index</b>	The following metrics provide information about slave events, slave counts, and slave states.		
<b>Task index</b>	The following metrics provide information about active and terminated tasks. A high rate of lost tasks may indicate that there is a problem with the cluster.		
	Field name	Data type	Description
	tasks_error	Double	Number of tasks that were invalid
	tasks_failed	Double	Number of failed tasks
	tasks_finished	Double	Number of finished tasks
	tasks_killed	Double	Number of killed tasks
	tasks_lost	Double	Number of lost tasks
	tasks_running	Double	Number of running tasks
	tasks_staging	Double	Number of staging tasks
	tasks_starting	Double	Number of starting tasks
<b>Framework index</b>	The following metrics provide information about the registered frameworks in the cluster.		
<b>Message index</b>	The following metrics provide information about messages between the master and the slaves and between the framework and the executors. A high rate of dropped messages may indicate that there is a problem with the network.		

### 3.3 Data management

#### 3.3.1 Training dataset

The dataset is created by simulating frameworks that commonly used for Mesos cluster. The type of framework is divided into 3 types 1) Application management and batch scheduling, 2) Data processing, and 3) Distributed databases and storage. This project will cover only first two types of framework. It Implements a job simulator to submit frameworks that work well with Apache Mesos and used by many organizations. Nowadays, the simulator simulates based on following example typically job, shown in **Table 3.8** and the application job will run according to **Table 3.9** for one week, and the minimum task for a day is 50 for each framework.

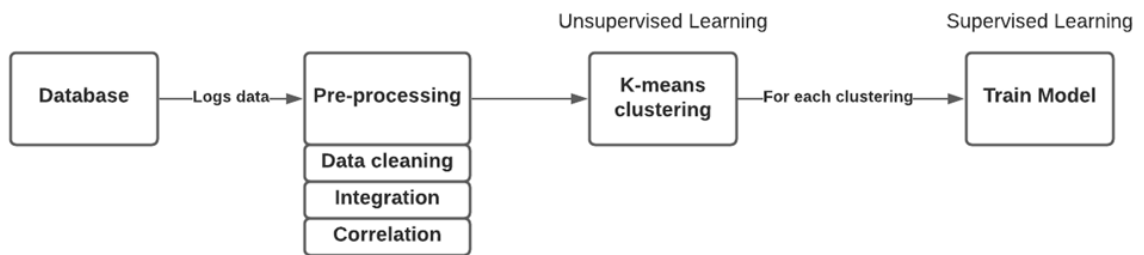
**Table 3.8** Framework of Apache Mesos.

Type of Framework	Framework1	Framework2	Framework3
1. Application management and batch scheduling	Chronos	Marathon	
2. Data processing			Spark

**Table 3.9** Application Data.

Framework	Application job
Chronos	Wordcount, Kmeans, Topk, and InvertedIndex
Marathon	Inline Shell Script and Docker based Application <a href="https://mesosphere.github.io/marathon/docs/application-basics.html">https://mesosphere.github.io/marathon/docs/application-basics.html</a>
Spark	Wordcount, Pi Estimation, and Text search <a href="http://spark.apache.org/examples.html">http://spark.apache.org/examples.html</a>

### 3.3.2 Data pipeline

**Figure 3.6** Data pipeline.

This project uses log data that mentioned before to build models by using the following steps below.

1. **Database:** Collecting logs data and sending out all of data from last week.
2. **Pre-processing:**
  - **Data cleaning:** Delete uncompleted and unused data.
  - **Integration:** Summarizing resource utilization of task, and server.
  - **Normalization:** Changing value of data into the same range, without distorting differences in the ranges of values.
  - **Data selection with correlation:** Finding correlation of each attribute and selecting high correlation to build a model.
3. **Data Mining:** There is plenty of data which are unable to identify their relationship, so this project plugs them all into K-means clustering algorithm. It will find data patterns by grouping the data into clusters. Assuming that each cluster is pointed to be a subset of the same machines, task, or framework. Each data cluster will be further investigated. The data will be input those same metrics into the machine learning model.

## CHAPTER 4 EXPERIMENTAL SETUP AND RESULTS

This chapter will discuss experimental environment setup for this experiment. The result from clustering data and result from random forest model to predict success rate of incoming task. The result from each policy to show fairness, number of failed tasks, CPU and memory utilization, and system load to show if each policy improve the performance.

### 4.1 Setup cluster, framework application, and parameter

For the experiment setup, cluster had setup inside a cloud provider which called Amazon Web Services (AWS). This cluster consists of 3 nodes with 2 CPUs, 2.8 GB of memory, and 45 GB of disk for each node as shown in **Figure 4.1**. This cluster was setup with 3 widely known framework: Mesos, Spark Marathon, and Chronos. The tests were conducted by simulated data with randomly varied resources of each task based on task characteristics.

Resources				
	CPU	GPU	Mem	Disk
Total	6	0	8.4 GB	135.0 GB
Allocated	0	0	0 B	0 B
Offered	0	0	0 B	0 B
Idle	6	0	8.4 GB	135.0 GB

**Figure 4.1** Resources of the cluster

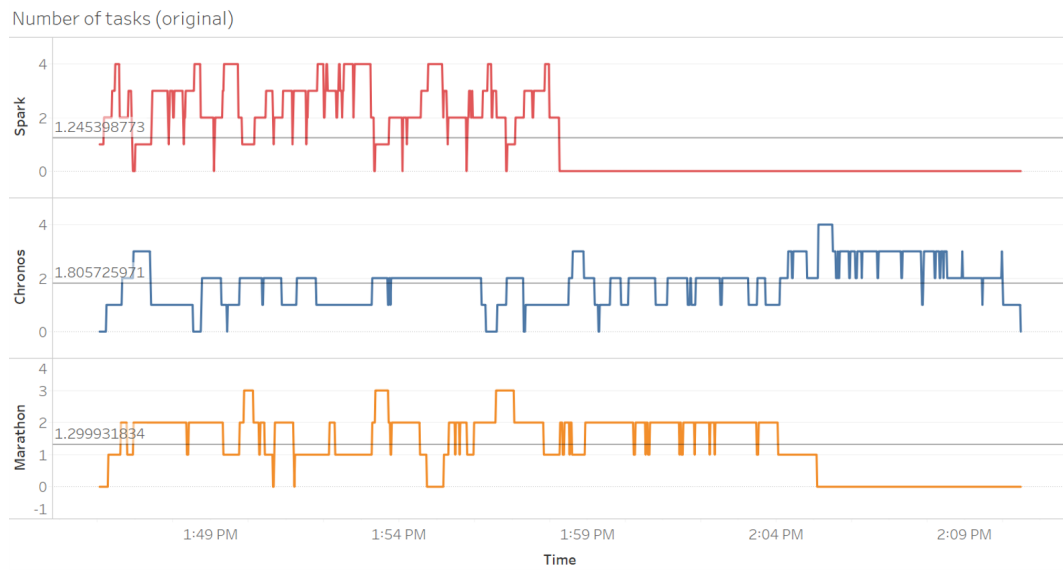
Simulated data was created by running sample jobs in a cluster following in **Table 4.1**.

**Table 4.1** Simulated task configuration.

Framework	Number of tasks	Arrival Rate (sec)
Marathon	33	2
Chronos	33	2
Spark	33	2

From **Table 4.1** show the number of tasks running in system to perform simulated task. The details about simulated task in each framework. Firstly, Spark consists of tasks that are implemented in Python-based. There are 2 basic tasks that use to query database and perform left and right join. Secondly, Chronos and Marathon have 3 types of tasks running in this system. All tasks consist of vary workload from minimum workload of text classification to maximum workload of training model and genetic algorithm. The result of submitted task is shown in **Figure 4.2**.





**Figure 4.2** Number of tasks for each framework

This project got the example of cluster metric data after running sample job in cluster and gathering cluster metric data as shown in **Figure 4.3**. Each row of cluster metric data was captured every 5 seconds, and each column of cluster metric data was an information of cluster, for example, CPU utilization, memory utilization, number of finished tasks, number of failed tasks, and other information.

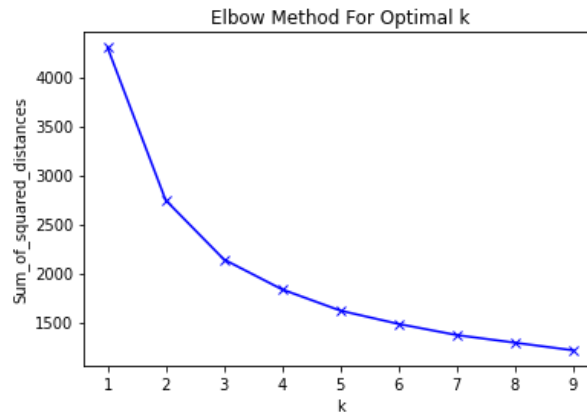
	A	B	C	D	E	F	G
1	_id	_index	_score	master/cpus_used	master/disk_used	master/frameworks_active	master/mem_used
2	QjeZhXcBc mesos_1		0	4.25	512	2	2,176
3	cSeZhXcBc mesos_1		0	4.25	768	2	2,304
4	cieZhXcBc mesos_1		0	4.25	768	2	2,304
5	oSeZhXcBc mesos_1		0	4.25	768	2	2,304
6	oieZhXcBc mesos_1		0	3.75	512	2	1,280
7	OSeZhXcBc mesos_1		0	4.5	512	2	1,408
8	OieZhXcBc mesos_1		0	4.5	512	2	1,408
9	ASeZhXcBc mesos_1		0	5.5	512	2	1,536
10	AieZhXcBc mesos_1		0	5.5	512	2	1,536
11	MSeZhXcB mesos_1		0	5.5	512	2	1,536
12	MieahXcB mesos_1		0	4	256	2	1,152
13	YSeahXcBc mesos_1		0	6	256	2	1,792
14	YieahXcBc mesos_1		0	5	256	2	1,664
15	kSeahXcBc mesos_1		0	5	512	2	2,560
16	kieahXcBc mesos_1		0	5	512	2	2,560
17	wSeahXcB mesos_1		0	5	512	2	2,560
18	wieahXcBc mesos_1		0	5	512	2	2,560
19	8SeahXcBc mesos_1		0	5.75	512	2	3,072
20	8ieahXcBc mesos_1		0	5.75	512	2	2,560
21	lSeahXcBc mesos_1		0	5.75	512	2	2,560
22	lieahXcBc mesos_1		0	5.75	512	2	2,560
23	USeahXcB mesos_1		0	5.75	512	2	2,560
24	UieahXcBc mesos_1		0	6	512	2	3,072
25	gSebhXcBc mesos_1		0	6	512	2	3,072
26	giebhXcBc mesos_1		0	6	512	2	3,072

**Figure 4.3** Example of cluster metric data

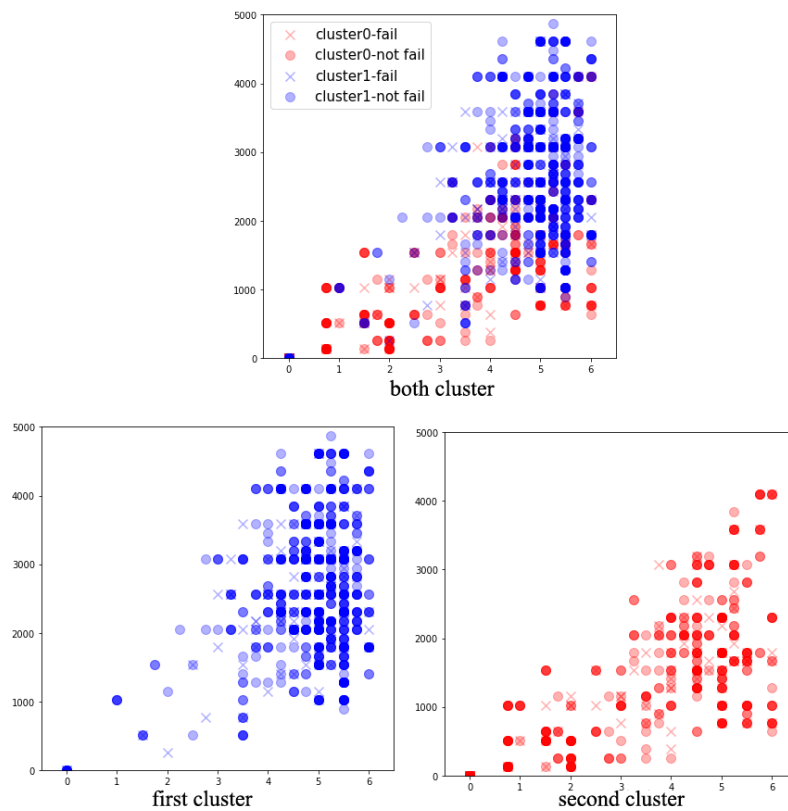
## 4.2 Model for predict success rate

### 4.2.1 Clustering

The metric data was clustered by using k-means algorithm and used elbow method to find optimal k parameter which is number of data cluster in k-means. The result is shown in **Figure 4.4**. From the graph,  $k = 2$  was chosen because at this point the distortion start to decrease in linear form. Therefore, the cluster metric data was separated into 2 clusters by k-means. After separated data into 2 clusters, it was expected that each cluster will be separated by resource utilization. But the result show that resource utilization cannot indicate the cluster they belong to as shown in **Figure 4.5**.

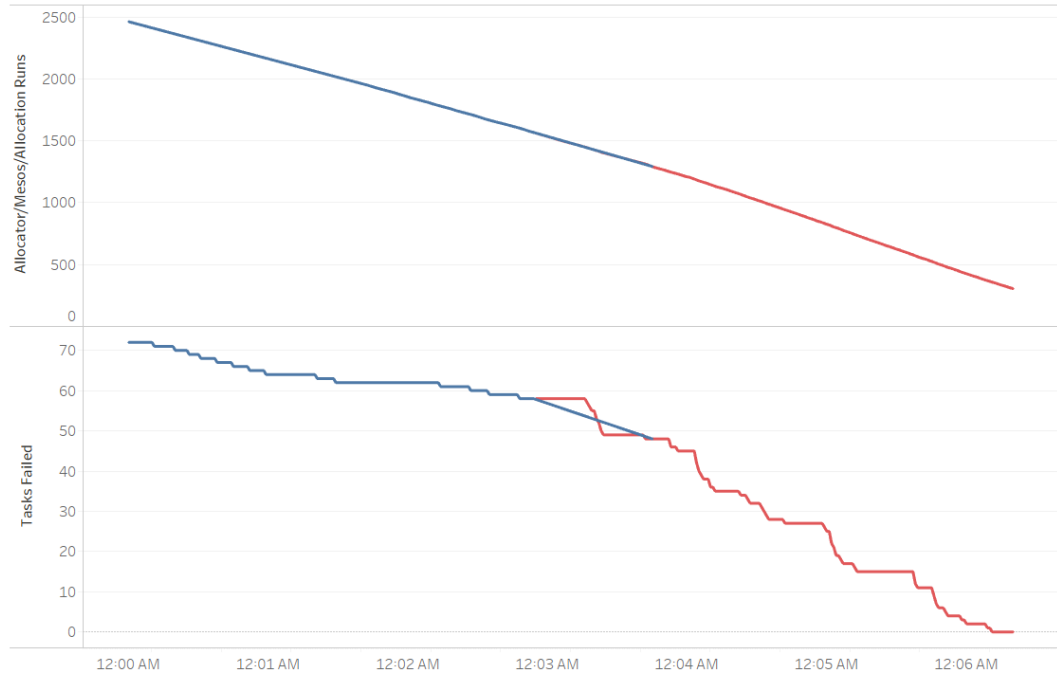


**Figure 4.4** Elbow method for optimal k

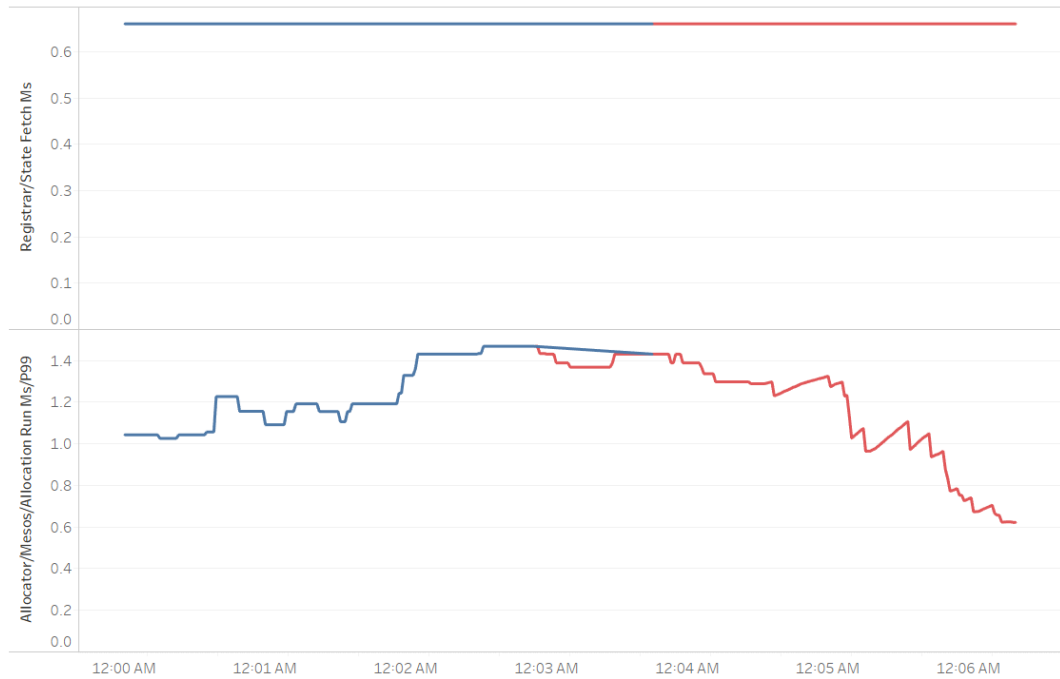


**Figure 4.5** Data clustering visualize by CPU and memory utilization

After searching for the characteristic of each cluster and plotting graph as shown in **Figure 4.6**, It was found that data were clustered by the time that is not applicable to predict success rate. About the correlation of all metrics to the number of failed tasks, the metrics that have high correlation are related to time, and the metrics that have low correlation are either constant or little change over time as shown in **Figure 4.7**.



**Figure 4.6** Data clustering visualize by metrics that have high correlation



**Figure 4.7** Data clustering visualize by metrics that have low correlation

### 4.2.2 Random forest model

Random forest model was trained with these following parameters:

1. **max\_dept**: The maximum dept of the tree sets to be 10
2. **random\_stat**: This parameter control randomness of the bootstrapping of the samples used when building tree. 10 is seed for generate random number. Using an integer will produce the same result across different calls. It is easier to check that the results are stable across a number of different distinct random seeds.
3. **ma\_features**: For each split, it will consider maximum 10 features.

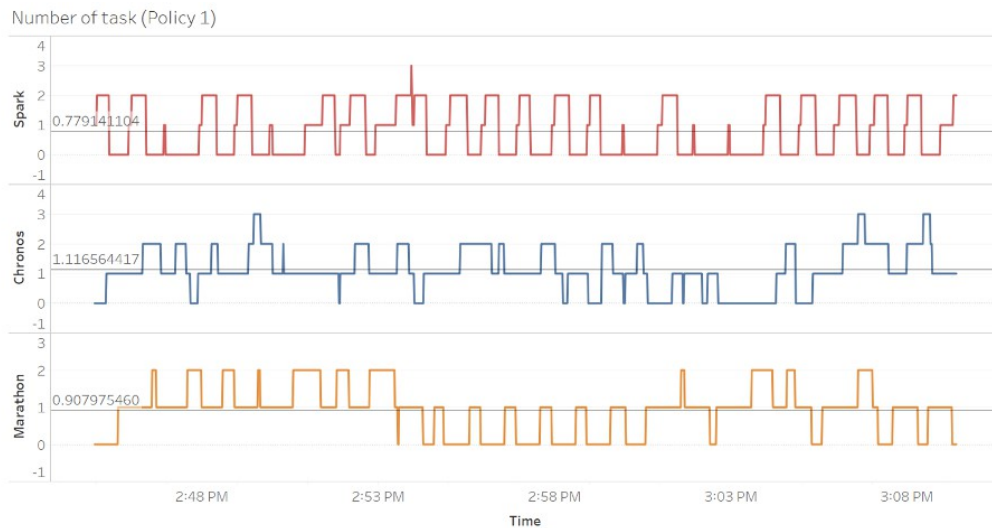
The result of random forest model is shown in **Table 4.2**. The accuracy of this model is 0.832, precision is 0.85 and recall is 0.98.

**Table 4.2** Result from random forest model.

	Fail (predicted)	Finish (predicted)
Fail (actuaterd)	317	6
Finish (actuaterd)	58	0

### 4.3 Policy 1: First Demand Share Policy (FDP)

FDP used the same setup as mentioned in **Section 4.1** and use the same submitted tasks in **Table 4.1**. NKR-scheduler has developed to receive tasks, and then considers based on the first policy.

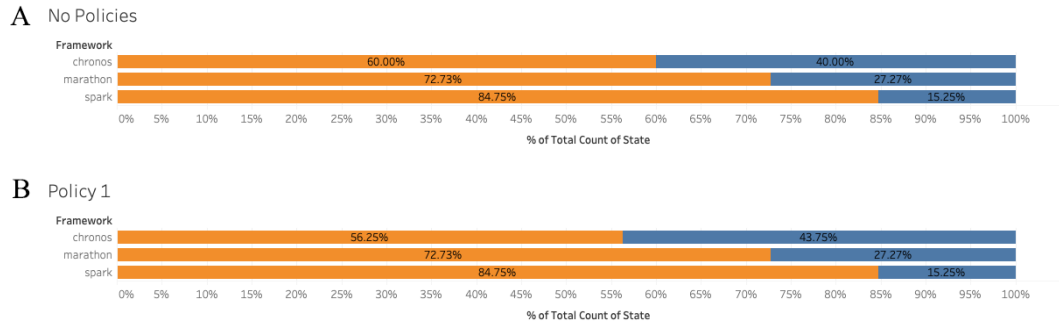


**Figure 4.8** Number of tasks for each framework after using FDP

From **Figure 4.2**, Marathon and Chronos could not launch a fair number of tasks because Spark could hold on to offer more than the others. After comparing with normal Mesos, there is a little improvement in fairness as shown in **Figure 4.8**. Each framework had almost the same approximate number of tasks, which is 1 task. The values that use to compare between before and after applied first policy was following with these values (0.77914, 1.1656, and 0.90797). After calculating the average of difference, the result is 0.257. So, this policy can improve fairness compared to the default policy 0.3736. The result is increased by 31.2% This project also considered these other matrices after applying this policy:

## 1. Failed task

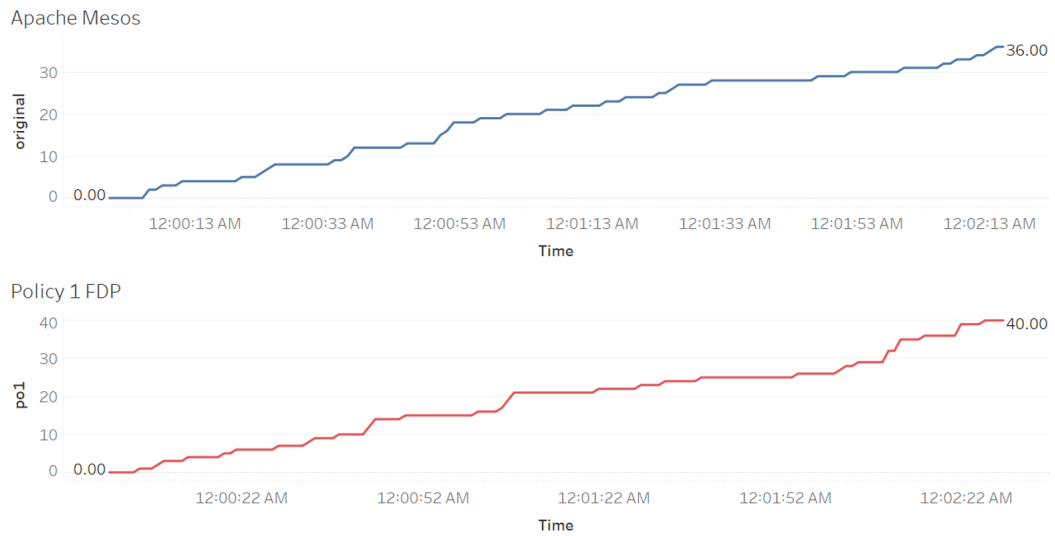
The result of finished and failed tasks for each framework before and after applied this policy is shown in **Figure 4.9**. The orange color shows percent of finished tasks and the blue one shows percent of failed tasks. The number of Chronos failed tasks was increased, but the number of Marathon and Spark failed tasks was the same. In **Figure 4.10** shows that growth rate of failed tasks is upward when used this policy. The slope was increased from 0.258 to 0.265. So, this policy not only cannot reduce the number of failed tasks but also increase its failure rate.



**Figure 4.9** Number of finished and failed tasks before and after using FDP

(A) is before using FDP and (B) is after using FDP

## Number of failed task



**Figure 4.10** Growth rate of fail task before and after using FDP

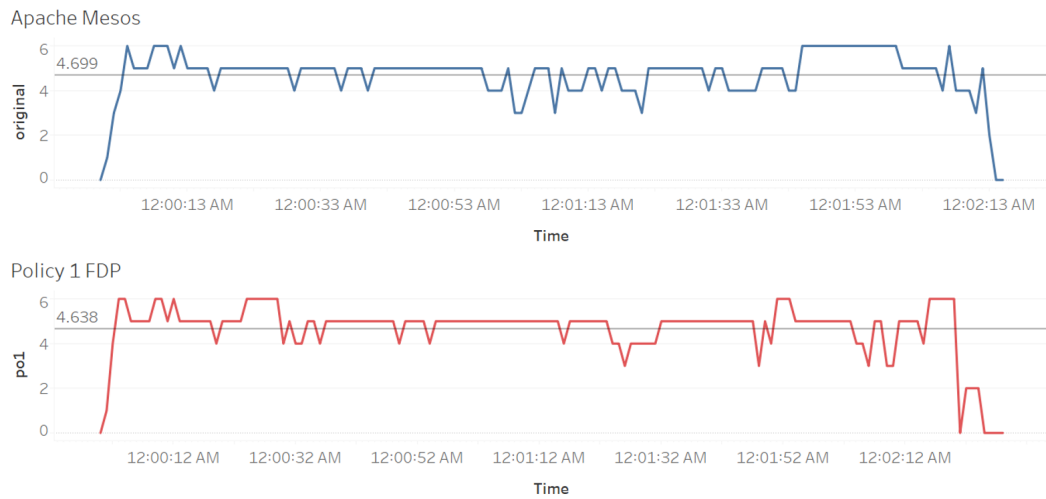
## 2. CPU and memory utilization

The averages of CPU and memory utilization of cluster framework before and after used this policy is shown in **Table 4.3**. From the table, both CPU and memory utilization average were increased after used this policy. The amounts of CPU and memory utilization before and after used this policy in each time is shown in **Figure 4.11** and **Figure 4.12**.

**Table 4.3** Average of CPU and memory utilization before and after using FDP.

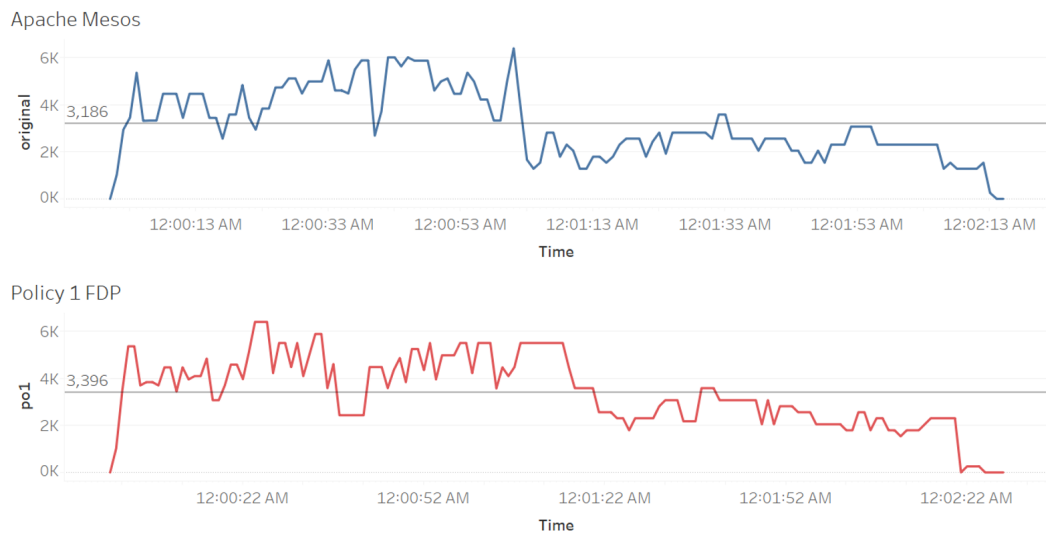
	Before	After
<b>CPU</b>	78.31%	77.30%
<b>Memory</b>	37.83%	40.43%

### CPU Utilization



**Figure 4.11** CPU utilization before and after using FDP

### Memory Utilization

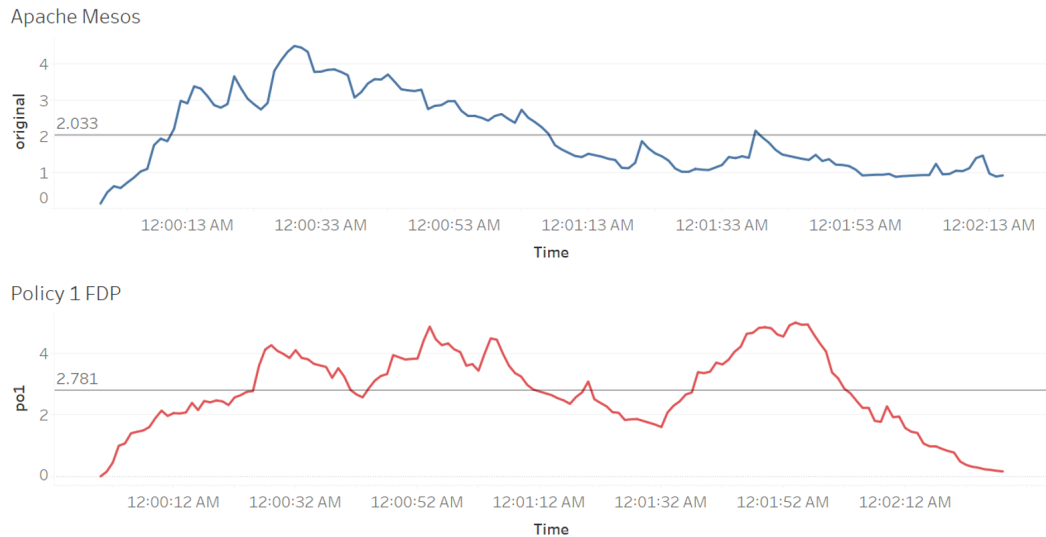


**Figure 4.12** Memory utilization before and after using FDP

### 3. System load

The result of system load in this cluster before and after used this policy is shown in **Figure 4.13**. System load average before using FDP is 2.033 and after is 2.781. So, system is busier when applied this policy.

#### System Load



**Figure 4.13** System load before and after using FDP

### Conclusion of First Demand Share Policy (FDP)

First Demand Policy can improve fairness of running tasks in a period of time. The number of failed tasks is still the same in the most of frameworks. Only Chronos failed task is decrease by 3.75%. Also, failure rate of failed tasks, resource utilization and system load are not improved.

## 4.4 Policy 2: Success Rate Prediction

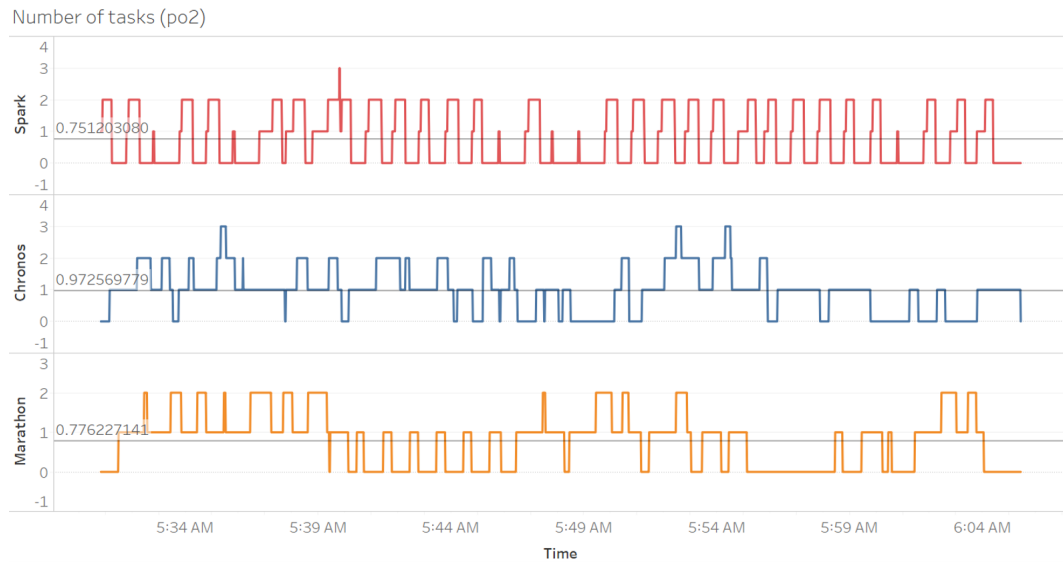
The result of submitted task is shown in **Figure 4.14**.

There is a little improvement in fairness as shown in **Figure 4.14**. Each framework had almost the same approximate number of tasks, which is 0.97. After calculating different average, the values are (0.7512, 0.9725, and 0.7762), the result is 0.147. So, this policy can improve fairness compared to the default policy 0.3736. Then it comes to the result of fairness improvement by 60.65% and the fairness increased by 42.8% when compare to FDP.

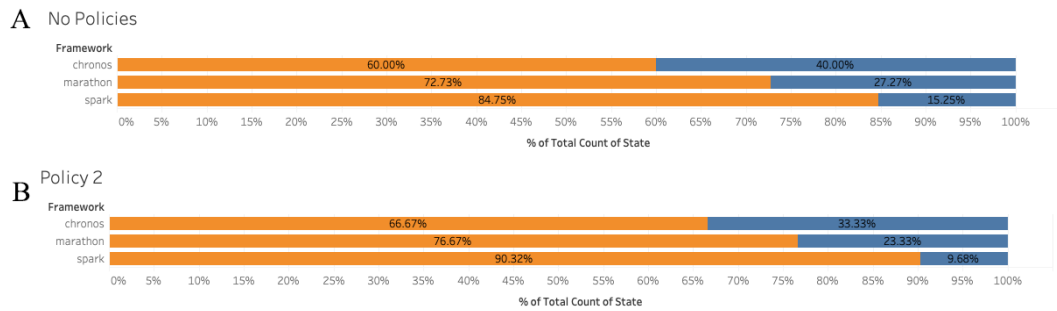
This project also considered these other matrices after applying this policy:

#### 1. Failed task

The result of failed and finished tasks for each framework before and after applied this policy is shown in **Figure 4.15**. The orange color shows percent of finished tasks and the blue one shows percent of failed tasks. The number of failed tasks in every framework was decreased. In **Figure 4.16** shows that growth rate of failed tasks is downward when used this policy. The slope was decreased from 0.258 to 0.152. So, this policy can reduce the number of failed tasks in every framework and decrease its failure rate.



**Figure 4.14** Number of tasks for each framework after using Success Rate Prediction



**Figure 4.15** Number of finished and failed tasks before and after using Success Rate Prediction

(A) is before using Success Rate Prediction and (B) is after using Success Rate Prediction

## 2. CPU and memory utilization

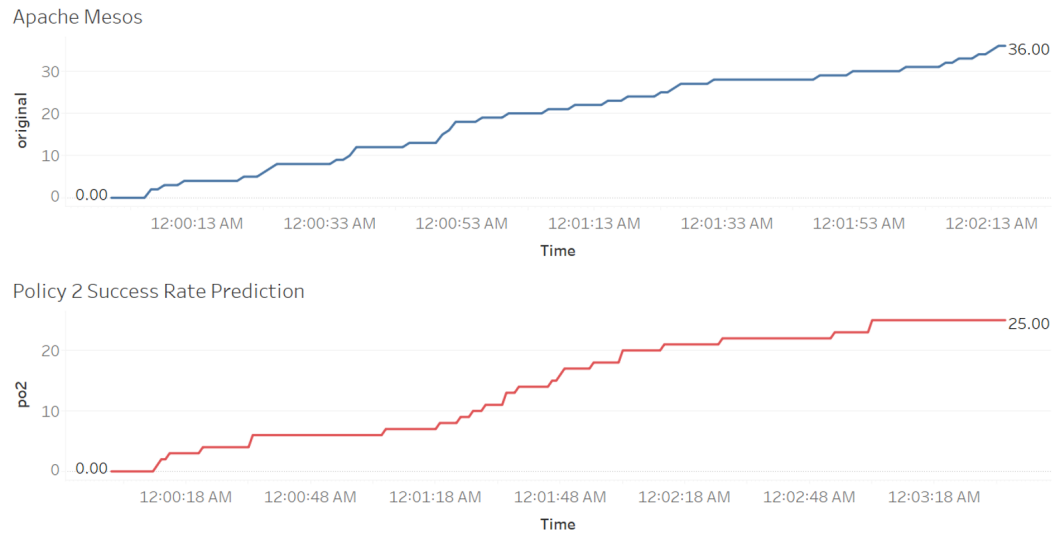
The averages of CPU and memory utilization of cluster framework before and after used this policy is shown in **Table 4.4**. From the table, both CPU and memory utilization average were decreased after used this policy. The amounts of CPU and memory utilization before and after used this policy in each time is shown in **Figure 4.17** and **Figure 4.18**.

**Table 4.4** Average of CPU and memory utilization before and after using Success Rate Prediction.

	Before	After
<b>CPU</b>	78.31%	41.67%
<b>Memory</b>	37.93%	23.32%

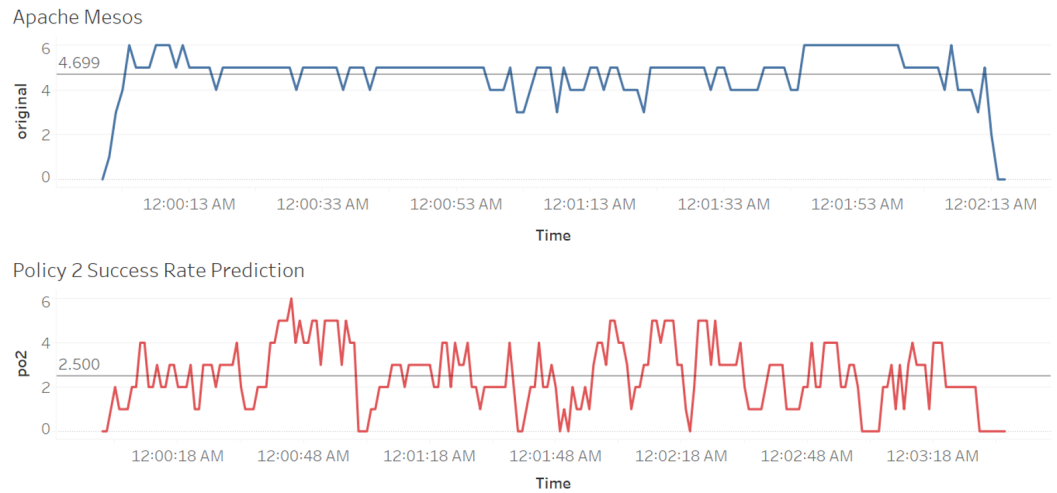


### Number of failed task



**Figure 4.16** Growth rate of fail task before and after using Success Rate Prediction

### CPU Utilization



**Figure 4.17** CPU utilization before and after using Success Rate Prediction

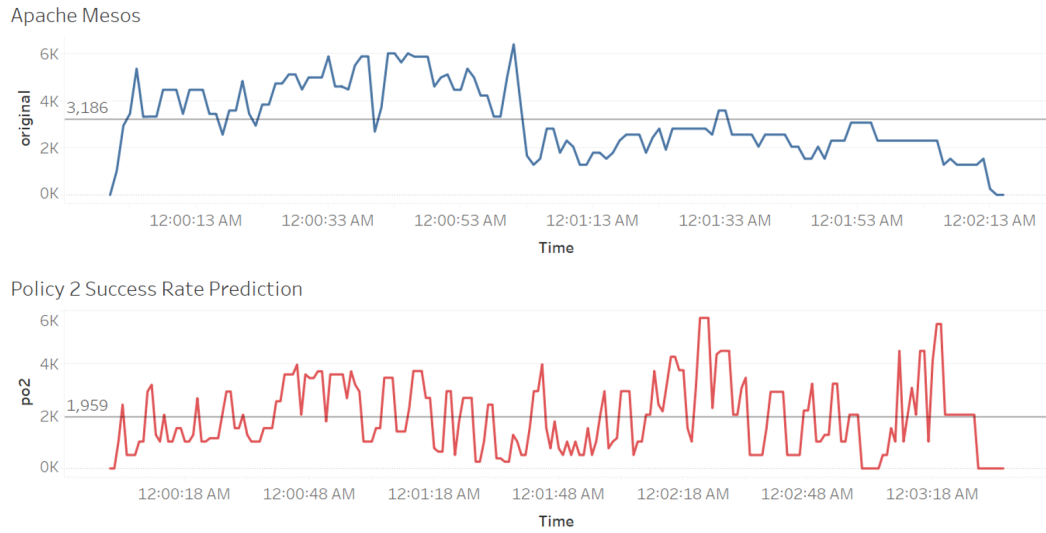
### 3. System load

The result of system load in this cluster before and after used this policy is shown in **Figure 4.19**. System load average before using Success Rate Prediction is 2.033 and after is 1.169. So, system is less busy when applied this policy.

### Conclusion of Success Rate Prediction

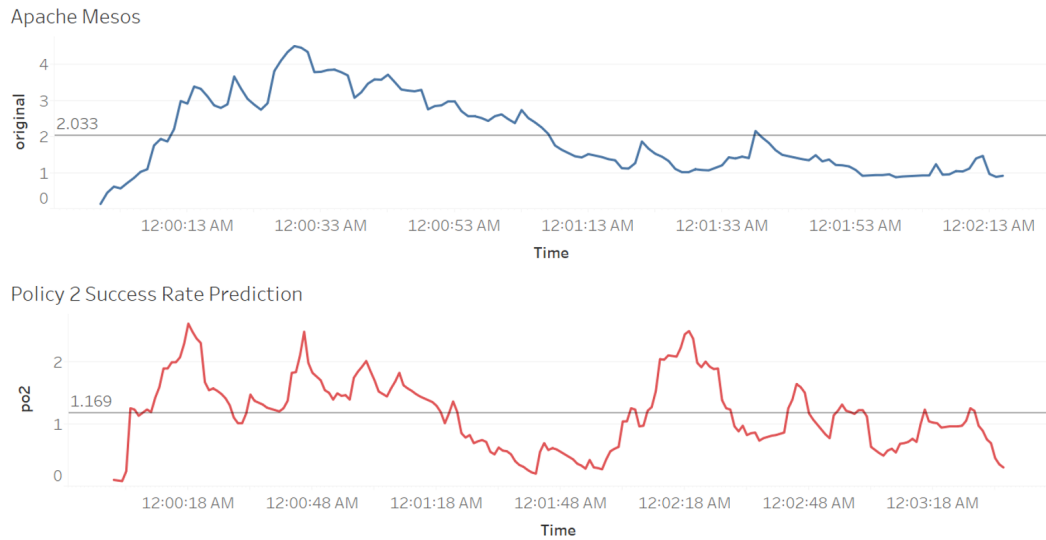
Success Rate Prediction can improve fairness of running tasks by only 60.65%. The number of failed tasks is decreased by 7.3%. Also, failure rate of failed tasks, resource utilization, and system load are improved.

### Memory Utilization



**Figure 4.18** Memory utilization before and after using Success Rate Prediction

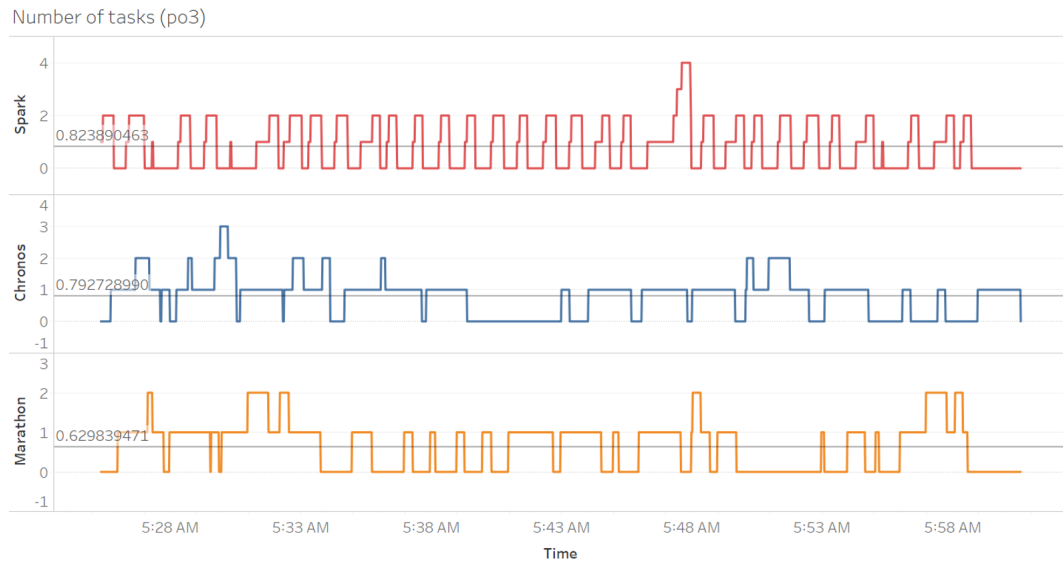
### System Load



**Figure 4.19** System load before and after using Success Rate Prediction

## 4.5 Policy 3: Hybrid Policy

Hybrid Policy is combined FDP and Success Rate Prediction. The result of submitted task is shown in **Figure 4.20**. In **Figure 4.20**, There is a little improvement in fairness as shown. Each framework had almost the same approximate number of tasks, which is 0.74. After calculated different average, the values are (0.823, 0.7927, and 0.6298), the result is 0.1293. So, this policy can improve fairness compared to the default policy 0.3736. Then it comes to the result of fairness improvement by 65.40%, compared to the first policy, the fairness improved by 49.68% and compared to the second policy, the fairness improved by 12%

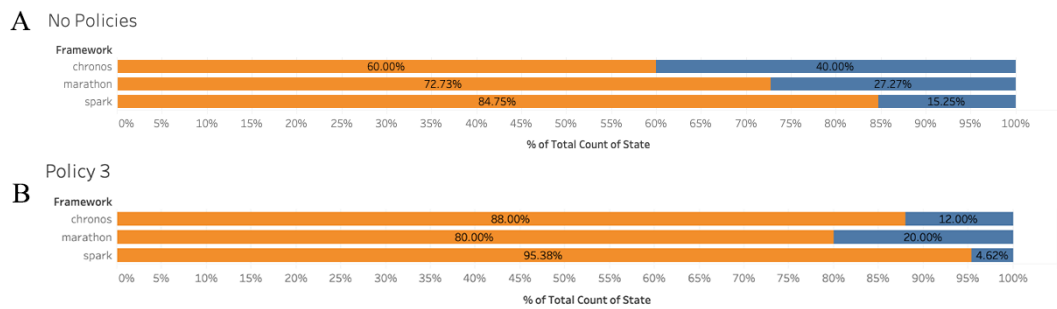


**Figure 4.20** Number of tasks for each framework after using Hybrid Policy

This project also considered these other matrices after applying this policy:

#### 1. Failed task

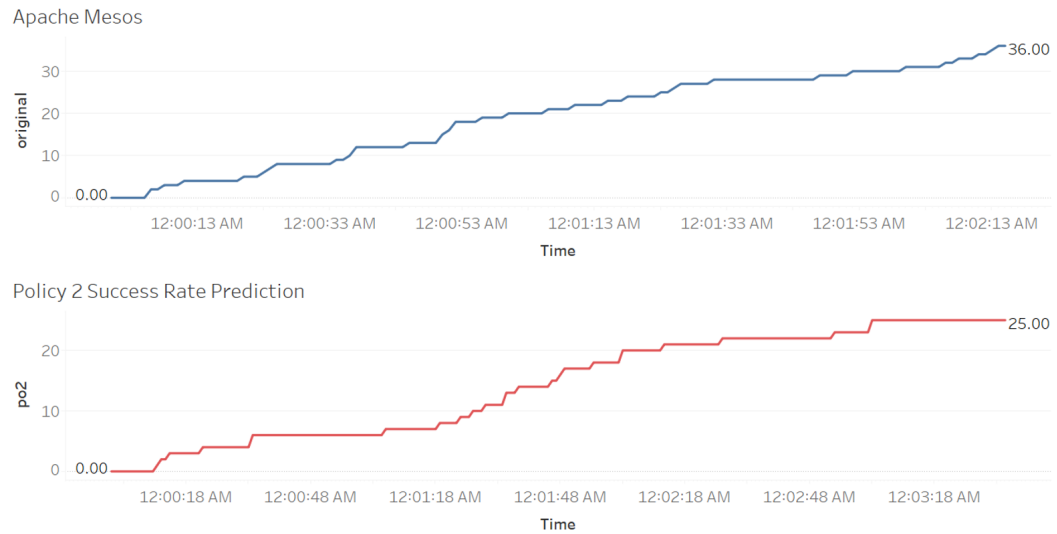
The result of failed and finished tasks for each framework before and after applied both policies is shown in **Figure 4.21**. The orange color shows percent of finished tasks and the blue one shows percent of failed tasks. The number of failed tasks in every framework was decreased by this policy. In **Figure 4.22** shows that growth rate of failed tasks is upward when used this policy. The slope decreased from 0.258 to 0.06. So, this policy cannot reduce the number of failed tasks in every framework and its failure rate.



**Figure 4.21** Number of finished and failed tasks before and after using Hybrid Policy

(A) is before using Hybrid Policy and (B) is after using Hybrid Policy

### Number of failed task



**Figure 4.22** Growth rate of fail task before and after using Hybrid Policy

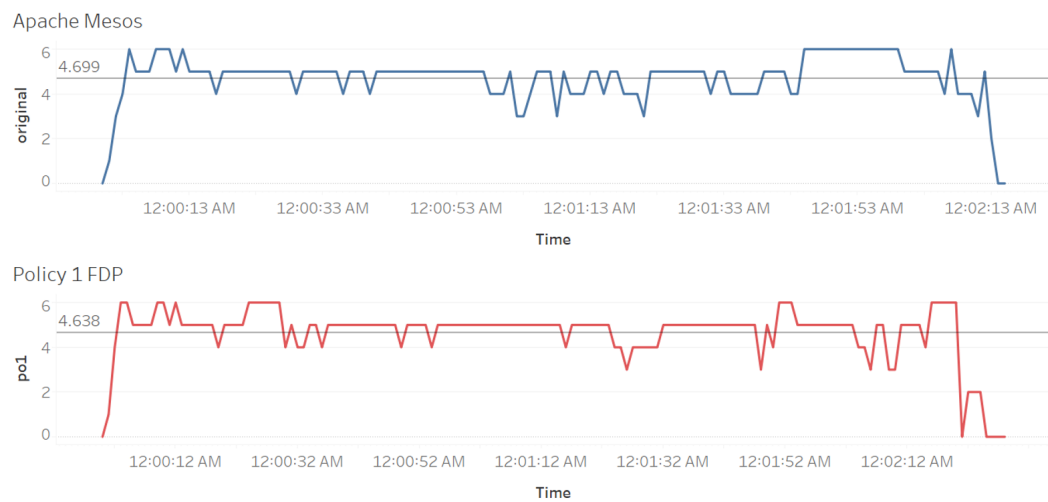
## 2. CPU and memory utilization

The averages of CPU and memory utilization of cluster framework before and after used this policy is shown in [Table 4.5](#). From the table, both CPU and memory utilization average were decreased after used this policy. The amounts of CPU and memory utilization before and after used this policy in each time is shown in [Figure 4.23](#) and [Figure 4.24](#).

**Table 4.5** Average of CPU and memory utilization before and after using both FDP and success rate prediction.

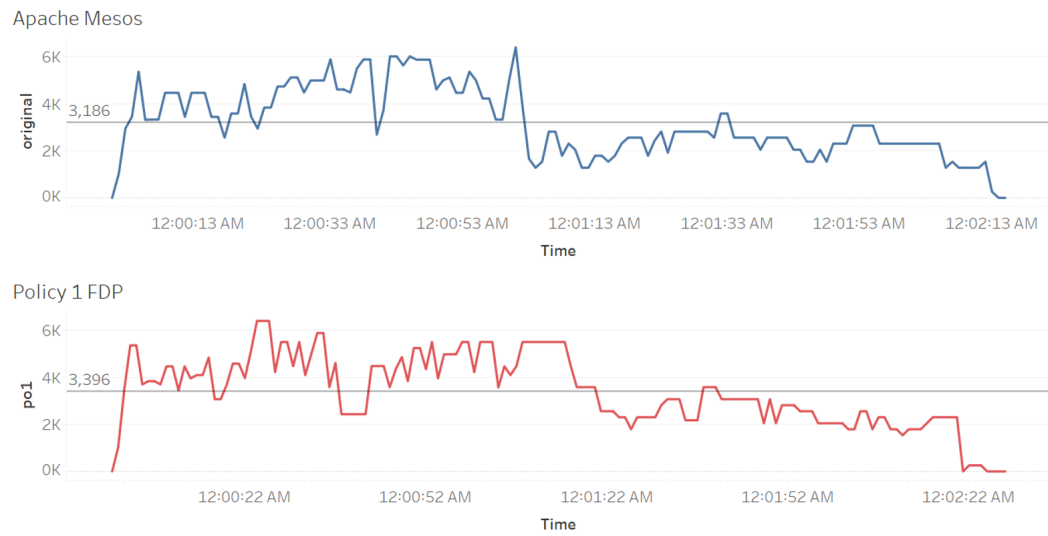
	Before	After
<b>CPU</b>	78.31%	39.12%
<b>Memory</b>	37.93%	24.21%

### CPU Utilization



**Figure 4.23** CPU utilization before and after using Hybrid Policy

### Memory Utilization

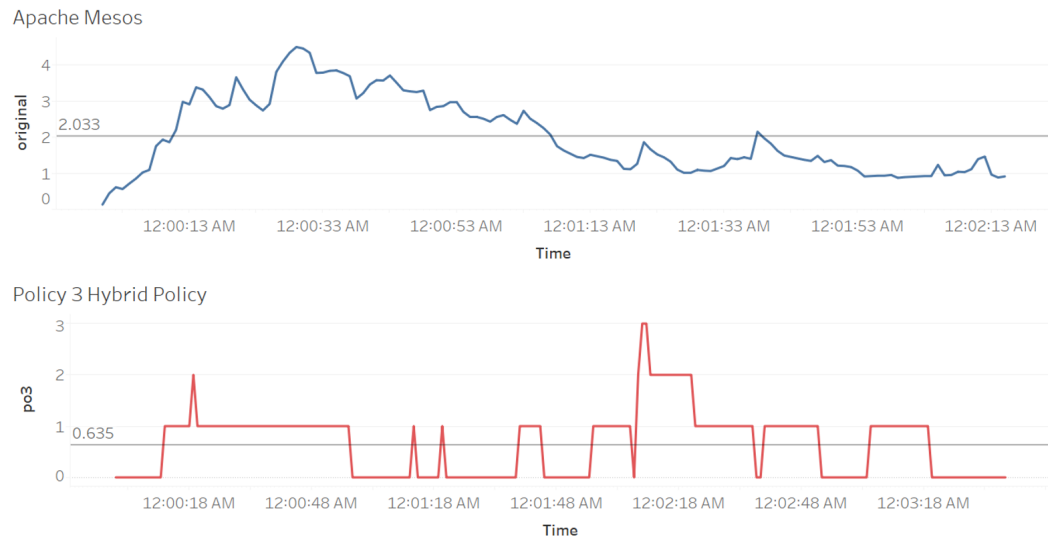


**Figure 4.24** Memory utilization before and after using Hybrid Policy

### 3. System load

The result of system load in this cluster before and after used this policy is shown in **Figure 4.25**. System load average before using FDP is 2.033 and after is 0.635. So, system is less busy when applied this policy.

### System Load



**Figure 4.25** System load before and after using Success Rate Prediction

## Conclusion of Hybrid Policy

Hybrid Policy can achieve the best results in terms of failure task and other metrics. Fairness of running tasks is improved by 65.4%. The number of failed tasks is reduced by 15.3%. Also, failure rate of failed tasks, resource utilization, and system load are improved.

## 4.6 Summary of Result

**Table 4.6** Result of all metrics from Apache Mesos with and without apply each policy of NKR-scheduler.

Policy	Number of failed tasks (tasks)	Fairness	Average of CPU utilization	Average of Memory utilization	Average of System load (tasks)	Running Time(min)
Original Apache Mesos	36	0.3736	78.31%	37.93%	2.033	24.26
First demand policy	40	0.257	77.30%	40.43%	2.781	24.26
Success Rate Prediction	25	0.147	41.67%	23.32%	1.169	34.37
Hybrid Policy	11	0.1293	39.12%	24.21%	0.635	35.17

The [Table 4.6](#) is shown result of all metrics from original Apache Mesos and Apache Mesos applied with each policy of NKR-scheduler. When FDP was applied, the fairness algorithm not only improves fairness from 0.3736 to 0.2570 but also increases unfavorable failed tasks and average CPU utilization. In order to reduce the failed tasks, Random forest model in Success Rate Prediction was applied instead. The results are improved by reducing number of failed tasks, increasing fairness to 0.1470, and lowering memory utilization to 23.32%, but in the other hand, the running time is extended which is the trade-off between running time and the other metrics. The improvement of fairness causes CPU utilization and system load to be decreased because tasks can be distributed better. After combine both policies to be Hybrid Policy, the tasks in queue will be run by fairness algorithm to reduce failed tasks and the resource will be modified by model that predicts success rate. This Hybrid Policy can reduce number of failed tasks significantly. The running time of Success Rate Prediction and Hybrid Policy is more than the others because they need more time to predict success rate of every incoming task before submitting.

## CHAPTER 5 CONCLUSIONS

This chapter demonstrates the results and discussion from the test run with and without applying each policy of NKR-scheduler. There are the improvement steps to improve fairness and reduce number of failed tasks. However, there is more studies needed to understand the mathematics model underlie each policy.

### 5.1 Result and Discussion

Three policies attached to NKR-scheduler have been evaluated in this project. The tasks were submitted to NKR-scheduler. After **First Demand Policy** was applied, the fairness in system was improved by 31.2% and the other metrics such as CPU utilization, memory utilization, failure rate, etc., had no improvement. The result did not show performance improvement as expected, and it was found that fairness has a correlation with failure task. The second experiment applied **Success Rate Prediction**. The failure rate was decreased by nearly 7.3% and the other metrics were significantly improved. However, the failure rate reduction did not meet the criteria as expected, and the improvement of fairness was insignificant. Therefore, the last policy called **Hybrid Policy** was developed. The result shown that the failure rate was decreased by 15.3% and the other metric were also improved. After simulated task were scheduling, it was found that Spark was configured with a relatively greedier scheduling policy compared to the other frameworks. This type of scheduling can significantly affect the other frameworks to manage resources utilization. As a result, Spark can run more tasks at the beginning and come with the highest number of success tasks compared to other frameworks, whereas other frameworks required much more time to complete and caused higher failure rate.

In the result of First Demand Policy, it shown that the success rate decreased while the fairness still improve. Success Rate Prediction focused on predicting the failure rate of incoming tasks, and the result of this policy shown the improvement of success rate and fairness. Incoming tasks will have more time to classify the type of tasks and modify the resources utilization. Therefore, both increased time and fairness are two factors that directly affect to failure rate. The result of Hybrid Policy proved that these two factors can improve the success rate of tasks.

### 5.2 Conclusion

There are many factors that can cause task failure, for example, lack of resources or greedy framework receive resources more than its fair share resources. In this project, it proposes NKR-scheduler that can be used with adaptive policies. The policies mainly classify into three parts, fairness algorithm called First Demand Policy (FDP), AI for failure detection called Success Rate Prediction, and Hybrid Policy. FDP considers both demands of each framework and their dominant share that come from cluster monitoring to decide which task to be dispatched. Success Rate Prediction dispatch the incoming task based on random forest model by predicting the failure rate of task. Hybrid Policy combines previous two policies together. The simulation tasks are building model, genetic algorithm, SQL query and text classification with vary the resource on each task randomly. These tasks are typical data science tasks of each framework. So, this work found that Hybrid Policy decreased the number of failed tasks by 15.3%

### 5.3 Future work

There are some questions was found along the test run but still cannot find the answer in this project report. To clarify these questions, the future works are needed to do two things. First, finding the mathematics formula to prove how time and fairness factors affect the failure rate. Second, find the total run time when reconfigure Apache Mesos to resubmit the failed task and compare the result with Hybrid policy in order to find trade-off between resubmitted time and time using to predict incoming task.

To improve this project, extended the project by building new policy that design to check the available resources or using AI to check another metrics on each agent are the things that could do. Moreover, it would be useful for those who want to study about the trade-offs between demand aware scheduling in a production environment, where hundreds of agents configured.



## REFERENCES

1. Jonas DeMuro, 2019, "What is container technology?," [www.techradar.com/news/what-is-container-technology](http://www.techradar.com/news/what-is-container-technology), Accessed: 2020-08-30.
2. docker, 2020, "What is a Container?," [www.docker.com/resources/what-container](http://www.docker.com/resources/what-container), Accessed: 2020-08-30.
3. expertsystem, 2020, "What is Machine Learning? A definition," <https://expertsystem.com/machine-learning-definition/>, Accessed: 2020-08-30.
4. Jake Frankenfield, 2020, "Artificial Neural Network (ANN)," <https://www.investopedia.com/terms/a/artificial-neural-networks-ann.asp>, Accessed: 2020-09-05.
5. Ali Ghodsi, Matei Zaharia, Benjamin Hindman, Andy Konwinski, Scott Shenker, and Ion Stoica, 2011, "Dominant resource fairness: fair allocation of multiple resource types," **8th USENIX conference on Networked systems design and implementation**, pp. 323–336, march 2011.
6. Ali Ghodsi, Matei Zaharia, Benjamin Hindman, Andy Konwinski, Scott Shenker, and Ion Stoica, 2011, "Mesos: A Platform for Fine-Grained Resource Sharing in the Data Center," **8th USENIX conference on Networked systems design and implementation**, April 2011.
7. IBM, 2020, "Apache ZooKeeper," <https://www.ibm.com/analytics/hadoop/zookeeper>, Accessed: 2020-09-05.
8. Roger Ignazio, 2016, **Mesos in Action**, Manning Publications Co.
9. Anton Kirillov, 2016, "Resource Allocation in Mesos: Dominant Resource Fairness," <http://datastrophic.io/resource-allocation-in-mesos-dominant-resource-fairness-explained>, Accessed: 2020-09-5.
10. Qing Liu, Tomohiro Odaka, Jousuke Kuroiwa, and Hisakazu Ogura, 2013, "A Fair Scheduling Algorithm for Adaptive Heterogeneous Resources in Data Centers," **IEICE**, pp. 872–885, April 2013.
11. Wenbin Liu, Ningjiang Chen, Hua Li, Yusi Tang, and Birui Liang, 2018, "A Fair Scheduling Algorithm for Adaptive Heterogeneous Resources in Data Centers," **the Tenth Asia-Pacific Symposium**, September 2018.
12. Hargrave Marshall, 2019, "Deep Learning," <https://www.investopedia.com/terms/d/deep-learning.asp>, Accessed: 2020-09-03.
13. Abueg Ralf, 2020, "Elasticsearch: What It Is, How It Works, And What It's Used For," <https://www.knowi.com/blog/what-is-elastic-search/>, Accessed: 2020-11-24.
14. Pankaj Saha, Angel Beltré, , and Madhusudhan Govindaraju, 2019, "Tromino: Demand and DRF Aware Multi-Tenant Queue Manager for Apache Mesos Cluster," **2018 IEEE/ACM 11th International Conference on Utility and Cloud Computing (UCC)** 63-72, May 2019.
15. Mbarka Soualhia, Foutse Khomh, and Sofiène Tahar, 2018, "Adaptive Failure-Aware Scheduling for Hadoop," **2015 IEEE 34th International Performance Computing and Communications Conference (IPCCC)**, February 2018.
16. TheMathWorks, 2020, "What Is Deep Learning?," <https://www.mathworks.com/discovery/deep-learning.html>, Accessed: 2020-09-03.
17. Robbert van Renesse, Aage Kvalnes, Dmitrii Zagorodnov, and Dag Johansen, 2006, "Policies and Metrics for Fair Resource Sharing," **University of Tromsø**, January 2006.
18. Wikipedia, 2020, "Apache Kafka," [https://en.wikipedia.org/wiki/Apache\\_Kafka](https://en.wikipedia.org/wiki/Apache_Kafka), Accessed: 2020-11-25.