



**COST ANALYSIS OF CONTAINER TERMINAL OPERATION
USING DISCRETE EVENT SIMULATION: A CASE OF MODJO DRY
PORT**

M.Sc THESIS

ABRAHAM TAMENE DHUNFA

HAWASSA UNIVERSITY, HAWASSA, ETHIOPIA

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ABRAHAM TAMENE DHUNFA

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This is to certify that the thesis entitled “Cost Analysis of Optimizing Container Terminal Operation using Discrete Event Simulation: a case of Modjo Dry Port” submitted in partial fulfillment of the requirements for the degree of Master’s with specialization in Industrial Engineering & Logistics Management, the Graduate Program of the school of Industrial Engineering, and has been carried out by Abraham Tamene Dhunfa ID.No. GPIELMW/0001/12 under our supervision. Therefore, we recommended the student has fulfilled the requirements and hence hereby can submit the thesis to the school of Industrial Engineering.

.....

NAME OF MAJOR ADVISOR

SIGNATURE

DATE

.....

NAME OF CO-ADVISOR

SIGNATURE

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DECLARATION

I hereby declare that the work which is being presented in thesis entitled: “Cost analysis of Container terminal Operation by Discrete Event Simulation case of Modjo Dry Port” is original work of my own, has not been presented for a degree of any other university and that all sources of material used for the thesis has been appropriately acknowledged.

ABRAHAM TAMENE DHUNFA

SIGNATURE: _____

DATE: _____

HAWASSA UNIVERSITY, INSTITUTE OF TECHNOLOGY

HAWASSA, ETHIOPIA

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ABBREVAITIONS AND ACRONYMS

CDT	Container Dwell Time
CT	Container Terminal
CTO	Container Terminal Operations
DES	Discrete Event Simulation
EC	Empty Containers
ESLSE	Ethiopian Shipping and Logistics Services Enterprises
ETB	Ethiopian Birr
FC	Full Containers
FEU	Forty foot Equivalent Unit
IBM	Industry Bench Mark
IT	Information Technology
KPI	key performance Indicators
MDP	Modjo Dry Port
OvS	Optimization via Simulation
SO	Simulation Optimization
TEU	Twenty foot Equivalent Unit
TOS	Terminal Operating System
Ycs	Yard Cranes

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ABSTRACT

A container terminal operation in MDP is a system with several subsystems and a large number of decisions for each subsystem. Due to the interactions of these subsystems, there is a lot of stochastic influence and interdependencies within the decisions which make an optimized operation of a whole container terminal very hard and without technical and methodical support hard to handle. One optimal operated subsystem influences all other subsystems and therefore does not result in optimality for the whole system. The research thesis focuses on analyzing the containers terminal operations at a terminal truck gate system, train side operations and yard side operations. To analyze the operations in an overall system with all its stochastic influence and interactions the method of simulation is used in this thesis, which provides the opportunity to create an experimental model and identify the best recommended course of action .The method in the data collection was a time measurement, simulations and document extraction was done. The developed simulation model which permits the modeling and simulation of container flows in a container terminal by truck and train. The new configuration of resources has brought 12% reduction of the total cost. The thesis found that MDP should work 18 hours a day for overall optimality than 12 hours a day as proved in scenarios. The optimal cost of system was found to be ETB 1,426,646.55 given that each resource assigned per respective position in September 2021. If it cannot optimize the total cost of the system MDP CTO in higher depth and details, the competitiveness and logistics hub of MDP will incur a lot of cost and time. More research and innovation are needed to keep CTO running at minimal cost while still providing required services for both trucks and trains.

Keywords: Optimization via Simulation; Container Terminal Operations; Key Performance Indicator, Discrete Event Simulation, Cost Analysis

CHAPTER ONE

1. INTRODUCTION

1.1. Background of the study

Over the last years, international sea freight container transportation has grown dramatically and container terminals play a key role within the global shipping network. Terminal's operations have received increasing interest in the scientific literature and operations research techniques are more and more used to improve efficiency and productivity (Aravindan & Thiruvengatasamy, 2016). Port efficiency is an important requirement in order to survive in the competitive world of shipping industry.

Ethiopia is one of landlocked country in Africa. Dry ports are important for landlocked country to enhance terminal operations, consume available resources wisely, and increase import and export (UNCTAD, 2018). Modjo Dry Ports (MDP) has been developed and operated since 2009. Modjo port and terminal is one of the largest operational inland dry ports in the country. The dry port is located in Oromia National Regional State Lome woreda at Modjo town. The port occupies a total area of 150 hectare while 63 hectare land area is used for container terminal services. Modjo Dry Port is located 73 Km from the capital and it is connected to the new Ethio – Djibouti Rail way line. As the largest port in the country, Modjo Dry Port handles more than 78 % of the nation's imports and has the capacity to accommodate 17,539 TEU containers at a time and its annual container handling capacity has reached up to 136,038 TEU (On et al., 2020).

Bekele & Ababa (2019) studied the assessment of the performance and the determinants factors for effective and efficient dry port performance by taking the case of Modjo Dry Port. Efficient and effective dry ports are crucial for the economic growth of a landlocked

nation like Ethiopia. They recommended the strategic leadership on the interventions of improving the performance of Modjo Dry Port.

Alo (2020) came with the study which explained the major challenges of multimodal transport system provisions in Modjo Dry Port were lack of essential equipment for cargoes handling, low level of technology, frequent theft, delay and congestion of cargo; un-automated service and, Modjo Dry Port has not sufficient capacity to (Port, 2020) accomplish the activity of the system successfully.

The major problem observed in Modjo Dry Port were cargo delays and waiting times at dry port, as hinterland conditions, technological advancement, and crane assignment, getting optimum system total cost and system number out were identified as Modjo Dry Port operations challenge. These challenging factors have great impacts on the terminal operations of Modjo Dry Port. Due to these impediments, the Modjo Dry Port terminal operation was found to be poor (Port, 2020). Container terminal operation in MDP is a system with several subsystems and a large number of decisions for each subsystem like: terminal operations at a terminal truck gate system, train side operations and yard side operations. Modjo Dry Port faces several challenges, which have a significant impact on its container terminal operations. One of the great challenges of ports it is how to measure their terminal operations (Port, 2020).

. It attempted to answer waiting line performance, modeled the container terminal operations and finally attempted to minimize the cost of the CTO under the objectives of the study .

The method of the study was optimization via simulation, specifically optimization using simulation is to examine the waiting line performance, to trade off cost of service and

waiting, to assign optimal number of servers and to develop a working model for the container terminal operation. Mazouz et al. (2017) investigated the role of computer simulation in evaluating the performance of a container terminal. Sharp et al., (2016) used future demand scenarios to design the characteristics of different terminals, developing a microscopic simulation model, while Gambardella et al. (1998) show how operation research techniques can be used to generate resource allocation plans. With the development of the theory and methods of simulation optimization and the computing technology, simulation optimization is receiving considerable attentions and tremendous achievements have been obtained.

With the use of simulation, the risk involved in working on the real system was avoided; it is easier, less costly and safer to change a representative of a system than to change the system itself.

The findings of the work were developed simulation model which provided better understanding of waiting lines performances. The model balanced the cost of waiting with respect to services provided and gave the optimum total cost of system and system number out. The study answered best scenario for the current activity and optimized the resources to attain competitiveness.

1.2.Statement of the problem

A container terminal works under multiple operational objectives. Container terminal operations comprise of a very complicated set of container handling process.

The major problem observed in Modjo Dry Port was getting optimum system total cost as Modjo Dry Port operations challenge. Theses challenging factors have great impacts on the terminal operations of Modjo Dry Port. Due to these impediments, the Modjo Dry Port

terminal operation was found to be poor based on bench of Industry Benchmark of ports (Port, 2020). Container terminal operation in MDP is a system with several subsystems and a large number of decisions for each subsystem like: terminal operations at a terminal truck gate system, train side operations and yard side operations. Modjo Dry Port faces several challenges, which have a significant impact on its container terminal operations. One of the great challenges of ports it is how to optimize their container terminal operations.

Many approaches have been developed to solve container terminal problems. Caceres et al. (2015) studied Modeling and Simulation of Berthing Processes for a Panamanian Container Terminal using BPMN and Discrete Event Simulation. Meng et al. (2017) studied Impact Extraction of Mega Vessels on Container Terminal Operations. Benedicto et al. (2019) studied a decision support tool for port planning based on Monte Carlo simulation. Said (2015) worked on the efficiency of container terminals depends on the container handling time in the terminal and in container terminals, many combinatorial related problems and the solution of one of the problems may affect to the solution of other related problems. Alo (2020) proved that Modjo Dry Port has not sufficient capacity to accomplish the activity of the system successfully. Bekele & Ababa (2019) suggested the strategic leadership on the interventions of improving the performance of Modjo Dry Port.

Many approaches have been developed to solve container terminal problems separately. Container terminal operation in MDP is a system with several subsystems and a large number of decisions for each subsystem like: terminal operations at a terminal truck gate system, train side operations and yard side operations. As such, they are unable to ensure optimal solution for container handling problems in container terminal. In this thesis, it was suggested that an optimization methodology for solving container handling problems

using simulation. Simulation-optimization methods have emerged as an approach to find optimal values for input variables that maximize certain output metric(s) of the simulation (Henesey, 2006).

1.3. Research questions

This research explored the following questions, and analyzed the dry port container terminal operations.

- I. What a waiting line performance parameters to be estimated via simulation?
- II. What a working model for container terminal operation?
- III. What an optimum cost to run the container terminal operation?

1.4. Objectives of the study

1.4.1. General objective:

The general objective of the study was to optimize container terminal operation using simulation which is a case of Modjo Dry Port.

1.4.2. Specific objectives

The specific objectives of study were:

- I. To examine the waiting line performance of container terminal operation via simulation.
- II. To develop a simulation model for the container terminal operation.
- III. To optimize the total cost of container terminal operation

1.5. Significance of the study

The studies have many advantages for all practitioners and academicians by providing useful information about an optimization of container terminal operation by simulation which is a case study of Modjo Dry Port. It will also be useful for all in logistics areas by providing information about the theoretical and actual decision making under support of simulation. The study may serve as an initiation for those who are interested to conduct a detailed and comprehensive study regarding the other dry port terminal operation in Ethiopia. Its significance can also be summarized in the following reasons:

- The model will help to assess waiting line performances, to optimize number of servers, to get optimum cost to run the container terminal.
- The study will go a long way to understand interaction operations at container terminal.
- The flexibility of the study is provided because it is easier, less costly and safer to change a representative of a system than to change the system itself.
- This study will save cost in terms of time and money
- With the use of simulation, the risk involved in working on the real system is avoided.
- The system of the real life system demands a representative model will ease the understanding of the model.

1.6. Scope of the study

The work focused on the Analysis of Optimizing Container Terminal Operation using Discrete Event Simulation, a case study of Modjo Dry Port which is the main terminal and port at national level. The queue discipline was used first in first out FIFO and the arrival was strictly random. It was considered statistically distributions for service rate and inter

arrival rate. The economic consideration for the queuing system was concern for the study to get optimum cost in keeping in balance of cost of service and waiting. Manipulation of a system using simulation concerns not only acceptance of input and generation of output but also to further examine the container terminal operations.

1.7.Organization of the study

The research thesis comprises five chapters. The first chapter outlines the introductory part including with the general background, statement of the problem, significance and objectives of the study and questions that would be answered by the study. The second chapter tells us the relative literature review of the study, which is mainly focuses on the a simulation model for Modjo Dry Port, which deals with the subject matter of the issue and related concepts essential to the study. The third chapter is about methodology, which tells us about the research design, case study, data collection method, and data extraction techniques. The fourth chapter is the input, process and output extraction of the research which deals with optimizing through simulation of container terminal operation. The fifth chapter is about the conclusions, recommendations and future works of the research works.

CHAPTER TWO

2. LITERATURE REVIEW

2.1.Theoretical background

2.1.1. Terminology

The definition of terms related to the topic is significant in helping readers to easily understand the concepts of these terms; they're interrelated elements, and relationships to each other, implications to circumstances and their impact to each other and other related variables.

- **System:** is a well-defined object in the real world under specific conditions, only considering specific aspects of its structure and behavior (Maria, 1997) .
- **Container terminal:** is a zone of the port where containers are loaded, unloaded and stored in a buffer area called yard. Inbound containers are unloaded from container careers train or truck by cranes and then transported by internal trucks to storage yard where they are stacked by yard cranes to their allocated positions waiting for the consignees to pick (Steenken et al., 2005).
- **Model:** a model is a representation of an actual system (Maria, 1997).
- **Dry Port:** is also known as an inland intermodal terminal directly connected to seaports with high capacity transports means, where customers can leave and pick up their standardized units as if dealing directly with a seaport(Roso & Lumsden, 2009).
- **Simulation:** Simulation can be broadly defined as a technique for studying real-world dynamical systems by imitating their behavior using a mathematical model of the system implemented on a digital computer (Maria, 1997).

- **Simulation model:** Simulation modeling is the process of creating and analyzing a digital prototype of a physical model to predict its performance in the real world (Maria, 1997).
- **Optimization:** mathematical technique for finding a maximum or minimum value of a function of several variables subject to a set of constraints, as linear programming or systems analysis .Queuing optimization model is to minimize the total cost of waiting cost and service cost(Jaisankar, 2018).

2.1.2. Container terminal at MDP

In general terms, container terminals can be described as open systems of material flow with two external interfaces. These interfaces are the train side with loading and unloading of trains, and the landside where containers are loaded and unloaded on/off trucks. Containers are stored in yard thus facilitating the decoupling of train side and landside operation. After arrival at the port, a truck/train is assigned to a berth equipped with cranes to load and unload containers. Unloaded import containers are transported to yard positions near to the place where they will be transshipped next. Containers arriving by road or railway at the terminal are handled within the truck and train operation areas. They are picked up by the internal equipment and distributed to the respective stocks in the yard. Additional moves are performed if sheds and/or empty depots exist within a terminal; these moves encompass the transports between empty stock, packing center, and import and export container stocks (Bekele & Ababa, 2019).

Trucks have a capacity of up to two TEU. At container terminals they are directed to transfer points where they are loaded and unloaded. To serve trains, railway stations with several tracks are part of container terminals. The capacity of one train is about 106 TEU.

The container storage area is usually separated into different stacks (or blocks) which are differentiated into rows, bays and tiers. Some stack areas are reserved for special containers like reefers which need electrical connection, dangerous goods, or over height/over width containers which do not allow for normal stacking. Often stacks are separated into areas for export, import, special, and empty containers (Bekele & Ababa, 2019). Figure 2.1 shows the shape of the dedicated area of yard at MDP CTO as follows:



Figure 2.1: Container terminal layout @ MDP (Google Earth)

The operational port performance can be measured by the following parameters(Martín Soberón, 2012):

- **Output:** it expresses the amount of cargo a terminal handles over a period of time, without specifying the resources utilized. When output is expressed in monetary units, financial indicators are built. Examples: Annual traffic or throughput (t/year; TEUs/year)
- **Productivity:** it is related to the work rate of the various resources a terminal has. That is, productivity can be defined as the amount of cargo (output) that a terminal

handles per unit of time and resource. Examples: Berthing facility productivity (TEUs/m y year); Vessel productivity at port (TEUs/h); Crane productivity (movements/h)

- **Utilization:** it is the ratio (expressed in percentage form) between the utilization of a given resource and the maximum utilization possible over a period of time. Examples: Berth facility utilization (% of occupancy)
- **Efficiency:** it is the utilization of ratios that express the coefficient between a result (output) – traffic- and a resource (input) –infrastructure and equipment.
- **Capacity:** it is the maximum traffic a port terminal can handle in a given scenario
- **Level of service:** It provides a measure of the quality perceived by system clients and users.

2.1.3. Components of system in MDP

To model and analyze a system, important components should be identified and defined(Taha, 2015).

- **Entity:** it is an object of interest in a system: Trucks and Trains
- **Attribute:** an attribute denotes the property of an entity: Quantity of trucks and trains
- **Activity:** any process causing changes in a system with a time period specified length: loading and unloading trucks/trains.
- **State of system:** the collection of variables necessary to describe a system at any time, relative to the objective of study. Busy/idle/in use cranes
- **Event:** an instantaneous occurrence that may change the state of the system: Arrival/departure of trucks or trains.

2.2.Related works

A container terminal works under multiple operational objectives. Container terminal operations comprise of a very complicated set of container handling process. Many approaches have been developed to solve container terminal problems.

Caceres et al. (2015) studied Modeling and Simulation of Berthing Processes for a Panamanian Container Terminal using BPMN and Discrete Event Simulation. The Business Process Modeling methodology is proposed as a tool to support the identification and visualization of the processes associated with container ships and participants in this process, followed by a discrete event simulation that generates the main performance indicators for this process area. The current model or "As is" model can result in "to be" or optimization model.

Meng et al. (2017) studied Impact Extraction of Mega Vessels on Container Terminal Operations. This study is concerned with the impact extraction of mega vessels on container terminal operations. First, the container operation process at a container terminal is formulated as a queuing network. Based on the queuing network, a simulation model is then developed. Because of the computational complexity of the simulation, the ARENA© software tool is used to solve the developed model, based on a realistic case involving the Hong Kong port.

Benedicto et al .(2019) studied a decision support tool for port planning based on Monte Carlo simulation. Generally, traditional methods involving empirical formulas or queuing theory can be useful though only for simple cases. In the case of systems, the problem needs to be approached from a holistic point of view, and more advanced methodologies should be considered. In such cases, simulation may be the most appropriate solution,

especially nowadays, when computation and data management are increasingly more efficient.

Said (2015) worked on the efficiency of container terminals depends on the container handling time in the terminal. He proposed an optimization methodology for solving container handling problems using genetic algorithm. The proposed methodology is applied on a real data from container terminal at Port-said Port in Egypt.

Kastner et al., (2021) worked on at container terminals, many cargo handling processes are interconnected and occur in parallel. This study analyzes simulation-based optimization, an approach that considers uncertainty by means of simulation while optimizing a given objective. The developed procedure simultaneously scales the amount of utilized equipment and adjusts the selection and tuning of operational policies.

Rezaei (2020) studied a simulation optimization model to make a better assignment of facilities cooperating in loading and unloading operation (LUO) at berth in order to minimize the ships waiting time. To validate the experiments, a real case study is taken. The case is one of the national container terminals in Iran named “ShahidRajae” which has been located near the Persian Gulf. Comparing the output of the model and real data implies the good efficiency of the model

Kotachi (2018) suggested that given the intensive computational effort that simulation optimization methods impose, especially for large and systems like container terminals, a favorable approach is to reduce the search space to decrease the amount of computation. A maritime port can consist of multiple terminals with specific functionalities and specialized equipment. Discrete-event simulation (DES) models are typically developed for and stochastic systems such as container terminals to study their behavior under different

scenarios and circumstances. Simulation-optimization methods have emerged as an approach to find optimal values for input variables that maximize certain output metric(s) of the simulation.

Alo(2020) said that in this contemporary world, multimodal transport system faces with various challenges to transport freight effectively in most landlocked developing country, causing lost economic grow and development. The limitations of freight transit facilitation that exists in these countries are frequent problems of Ethiopia, the case of Modjo Dry Port. Particularly, the study attempts to identify challenges of system provision, factors affecting operation of the system in Modjo Dry Port and role of Modjo Dry Port for the system to manage the problems in Ethiopia.

Bekele & Ababa (2019) studied the assessment of the performance and the determinants factors for effective and efficient dry port performance by taking the case of Modjo Dry Port. Efficient and effective dry ports are crucial for the economic growth of a landlocked nation like Ethiopia .Apart from this, the regression analysis of the study suggests that except infrastructure and machinery, information capital, human capital, service cost, size of the port and reliability found positive and significant determinants for the performance of the dry port at different levels of intensity and probability levels. The findings study implied that there is a possibility of improving the performance of Modjo Dry Port through capacitating human resources, ICT infrastructure, the size of the port and reconsidering the service cost and its reliability. Therefore, the study recommends the strategic leadership on the interventions of improving the performance of Modjo Dry Port.

2.3.Simulation and optimization

2.3.1. Introduction

Computers are well-suited for solving mathematical relationships involving large sets of variables. This capability sets them apart from humans; computers can be programmed to analyze relationships by solving the same equations hundreds or thousands of times. One of the best applications of this capability is system simulation. Here, a “system” can be anything that has one or more processes, with a set of inputs and a set of outputs. Simulation enables analysts to model a system and analyze what happens next i.e. what outputs are realized under different initial conditions (inputs). A good modeling and simulation methodology can result in accurate models, even when some parameters have a high degree of variability or uncertainty.

Simulation programming can employ simple simulation modeling techniques or, on the other hand, be extraordinarily. They are used to facilitate research in all academic disciplines, including meteorology, sociology, biology, physics, and engineering. Simulations are also extensively used by organizations to analyze various business processes.

Eiselt & Sandblom (2010) suggested a fast food restaurant scenario in their researches. By modeling different aspects of the restaurant (such as how many employees are working at any one time, how fast each one can serve customers their order, and how frequently customers come in for food), the restaurant “system” can be analyzed under various initial conditions to reveal its performance , such as: How long customers wait? What is the maximum number of customers waiting for service? How many customers can be serviced over the course of a business day? These performance metrics can be used to determine areas that can be improved to increase customer throughput and shop profitability. Another

well-known application of computers' number-crunching abilities is optimization. If the mathematical relationships between variables are known, a computer can optimize a parameter—that is, find the values of the input variables that maximize or minimize an output value. The mathematical expression that relates the inputs to the output is known as an “objective function. “So, for example, if the relationships among revenue, warehousing costs, transportation costs, and inventory costs are known for a given enterprise (or can be estimated), then the set of inputs that result in minimized total logistics cost can be determined.

2.3.2. Difference between simulation and optimization

Although simulation and optimization are similar and leverage many of the same computational techniques and algorithms, they are different activities. Each has its advantages and disadvantages, and each is better suited for certain types of problems. Here are some key differences between them:(Tekin & Sabuncuoglu, 2017)

- **“What-if” extraction:** Simulation is better suited to observing the performance of the simulated system by tweaking the initial conditions (that is, the values of the input variables). Optimization is used more often to determine an optimal system design.
- **Constraints:** Successful optimization depends on properly identifying the constraints placed on various parameters—for example; a business might have a maximum number of employees it can hire to work on production lines. With simulation, the analyst starts with realistic values for inputs and modifies them within reasonable ranges to determine what happens with the outputs.
- **Influence of randomness:** Simulations can account for random variation in the parameters—in the barbershop example, each barber's hair cutting speed can be

expressed as a normal distribution around an average. This variability can make a large difference in the accuracy of the results. Optimization works better clearly defined mathematical relationships that don't have variability.

- **Planning and decision support:** Optimization methods can be used to support both tactical and strategic planning decisions, because they provide a single “best” answer to a given problem. This is one of the advantages of optimization. Simulation, by contrast, is considered more exploratory.
- **Modeling difficulty:** Simulations are generally easier to model, because fewer assumptions need to be made. An optimization solution requires either more assumptions about the inputs or more computing power to deal with all the different variables to calculate the optimized result.

2.3.3. How simulation and optimization can work together

Although simulation and optimization help solve different problems, they can work together to drive business results. How? By application of simulation techniques for a system—say, the receiving dock at a warehouse—on the basis of observed factors that influence the efficiency, throughput, or other metrics of the receiving team, a business can get a feel for the factors that have the most pronounced effect on the outputs. Armed with these insights and data simulation techniques, the business can then make better assumptions about the mathematical relationships between the parameters, which drives better optimization—that is, better decisions about what to change and by how much to improve the team's performance (Carson & Maria, 1997).

2.3.4. Simulation in business

Data simulation tools are used in businesses of all sizes and in all industries to analyze current processes and determine where to focus on improvements. Here are some simulation system examples (Lee, 2015) :

- **Royal Dutch Shell:** used a simulation based model to support vessel servicing of offshore oil platforms, including factors such as vessel capacity, storage at port facilities, and more. The simulation showed Shell where best to invest in improvements.
- **Cancer center:** a major medical center in the Midwest modeled internal patient care processes. This helped them determine the best arrangement of different types of patient populations, thereby minimizing patient, doctor, and caregiver travel times and maximizing operating room utilization.
- **Agricultural logistics:** a sugarcane producer in Brazil used simulation to improve operational capacity and reduced capital costs, while increasing the efficiency of the vehicle fleet carrying sugarcane from plantation to mills.
- **Walmart:** Before investing millions into a robotic based system that picks groceries for its online grocery pickup system, Walmart ran a simulation to test viability before making the change.

In all simulation exercises, it's important to account for all the factors that influence the system's performance and to accurately characterize each one. Simulation modeling requires keen recording and data extraction—in some cases, large amounts of data—to get an accurate picture of the system. It's also important to validate the model by comparing model data with real system data. The better the model, the better the simulation's response to different inputs; good data modeling and simulation can result in

better optimization. Simulation and optimization can therefore be seen as two complementary approaches to solving business problems. With advances in big data simulation software and computing power, simulation and optimization will become increasingly important tools in every company's decision-making toolkit, enabling better insights and better business decisions (Banks et al., 2012).

Figure 2.2 shows the relationship of real world system, conceptual model and simulation model through validation and verification process. Through validation and verification the model eventually resembles more the real system.

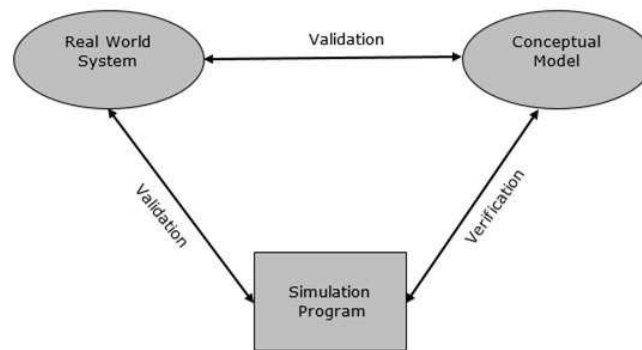


Figure 2.2: Simulation derived from real system (Mchaney, 2009)

2.3.5. Optimization and simulation in container terminal

The most difficult terminal management problem is optimizing the balance between the Truck and trains owners that are in need of quick service of their entities and economical use of allocated resources. Both container trucks/trains and container port facilities are very expensive; hence, it is most desirable to utilize them as intensively as possible.

The manager can trust the computer-generated solutions only by validating them by means of a simulation model of the environment of container terminal. Hence, the simulation tool also becomes a means to introduce new approaches into traditional settings. A simulation model of a container terminal is basically a computer program written in a general purpose

language (C/C++) or in a special simulation-oriented language – simulator (Arena, MES CTMS, Petri Nets, MODSIM)(Transport & Communication, 2010).

The simulation models are used to analyze bottle-neck and deadlock problems, conflicts, container handling techniques, vehicle and vessel scheduling (departure and arrival rates), equipment utilization and operational efficiency (yard, gate and berth). So, a simulation implements the most important aspects of the processes at the container terminal. The advantage of simulation modeling over analytical modeling of container terminals is that it allows for a greater level of detail and avoids too many simplifications.(Transport & Communication, 2010).

2.3.6. Statistically input data distributions for simulation model

There are many more different types of probabilistic distributions that we may actually encounter. Sometimes we may encounter these distributions only as a result of a computerized data fitting program. These types of programs are geared toward returning the best mathematical fit among many possible theoretical distributions. In these types of cases, a particular result does not necessarily mean that there is a rational reason why the data best fit a specific distribution. Sometimes a theoretical distribution that does make sense is may be as good as a fit. In these cases, we will have to decide whether it makes more sense to use the best mathematical fit or a very close fit that makes sense (Ungureanu et al., 2005).

Arena contains a set of built-in functions for generating random numbers from the commonly used probability distributions. These distributions appear on pull-down menus in many Arena modules where they're likely to be used. They also match the distributions in the Arena Input Analyzer. This Table describes all of the Arena distributions. Each of

the distributions in Arena has one or more parameter values associated with it. It should specify these parameter values to define the distribution fully. The number, meaning, and order of the parameter values depend on the distribution. A summary of the distributions (in alphabetical order) and parameter values are given in the Table 2.1 as follows:

Table 2.1: Statistically distributions (Ungureanu et al., 2005)

Summary of Arena's Probability Distributions		
Distributions		Parameter values
Beta	BETA	Beta,Alpha
Continuous	CONT	CumP ₁ ,Val ₁ ,...CumP _n Val _n
Discrete	DISC	CumP ₁ ,Val ₁ ,...CumP _n Val _n
Erlang	ERLA	ExpoMean,k
Exponential	EXPO	Mean
Gamma	GAMM	Beta,Alpha
Johnson	JOHN	Gamma, Delta,Lambda,X _i
Lognormal	LOGN	LogMean,LogStd
Normal	NORM	Mean,StdDev
Poisson	POIS	Mean
Triangular	TRIA	Min,Mode,Max
Uniform	UNIF	Min,Max
Weibull	WEIB	Beta,Alpha

2.4. Discrete event simulation model development

Discrete-event simulation (DES) is an established modeling technique within the realm of Operational Research, used widely for decision making (Liao et al., 2011). The following flow chart in Figure 2.3 clearly expresses how the discrete event simulation can be attained. The flow chart is well organized and addresses the objective of the study.

- **Problem formulation:** every study begins with a statement of the problem, provided by policy makers. Analyst ensures whether it is clearly understood. If it is developed by the analyst, the policy makers should understand and agree with it.

- **Setting of objectives and overall project plan:** the objectives indicate the questions to be answered by simulation. Determination should be made concerning whether simulation is the appropriate methodology. Assuming it is appropriate, the overall project plan should include: a statement of the alternative systems, a method for evaluating the effectiveness of these alternatives, plans for the study in terms of the number of people involved, cost of the study and the number of days required to accomplish each phase of the work with the anticipated results.
- **Model conceptualization:** it is very high level to identify the abstract essential features of a problem. How comprehensive should the model be? What are the state variables, which are dynamic, and which are important?
- **Data collection and model specification:** involves collecting and analysing the required input data. May involve equations, pseudo code, etc. How will the model receive input?
- **Model translation (computational model development):** involves the development of a computer program. Which is preferable to use a general-purpose programming language or a special-purpose simulation language?
- **Model verification:** it pertains to the computational model and checking its performance. Computational model should be consistent with specification model. If the input parameters and logical structure are correctly represented, verification is completed. Did we build the model right?
- **Model validation:** it is the determination that a model is an accurate representation of the real system. Achieved through calibration of the model, an iterative process of comparing the model to actual system behaviour. Is the computational model consistent with the system being analyzed? Did we build the right model?

- **Experimental Design:** If there are a significant number of system parameters, each with several possible values of interest, then the combinatory possibilities should be studied. The alternatives that are to be simulated must be determined. Decisions need to be made concerning: length of the initialization period, length of simulation runs and number of replication to be made of each run.
- **Production runs and analysis:** they are used to estimate measures of performance for the system designs that are being simulated. Important statistical extraction should be done to find the relationships between input and output parameters.
- **More runs:** given the extraction of runs that have been completed, the analyst determines if additional runs are needed and what design those additional experiments should follow.
- **Documentation and reporting:** two types of documentation: Program documentation and Process documentation
- **Program documentation:** can be used again by the same or different analysts to understand how the program operates. Further modification will be easier. Model users can change the input parameters for better performance.
- **Process documentation:** gives the history of a simulation project. The result of all extraction should be reported clearly and concisely in a final report. This enables to review the final formulation and alternatives, results of the experiments and the recommended solution to the problem. The final report provides a vehicle of certification.
- **Implementation:** success depends on the previous steps. If the model user has been thoroughly involved and understands the nature of the model and its outputs, likelihood of a vigorous implementation is enhanced.

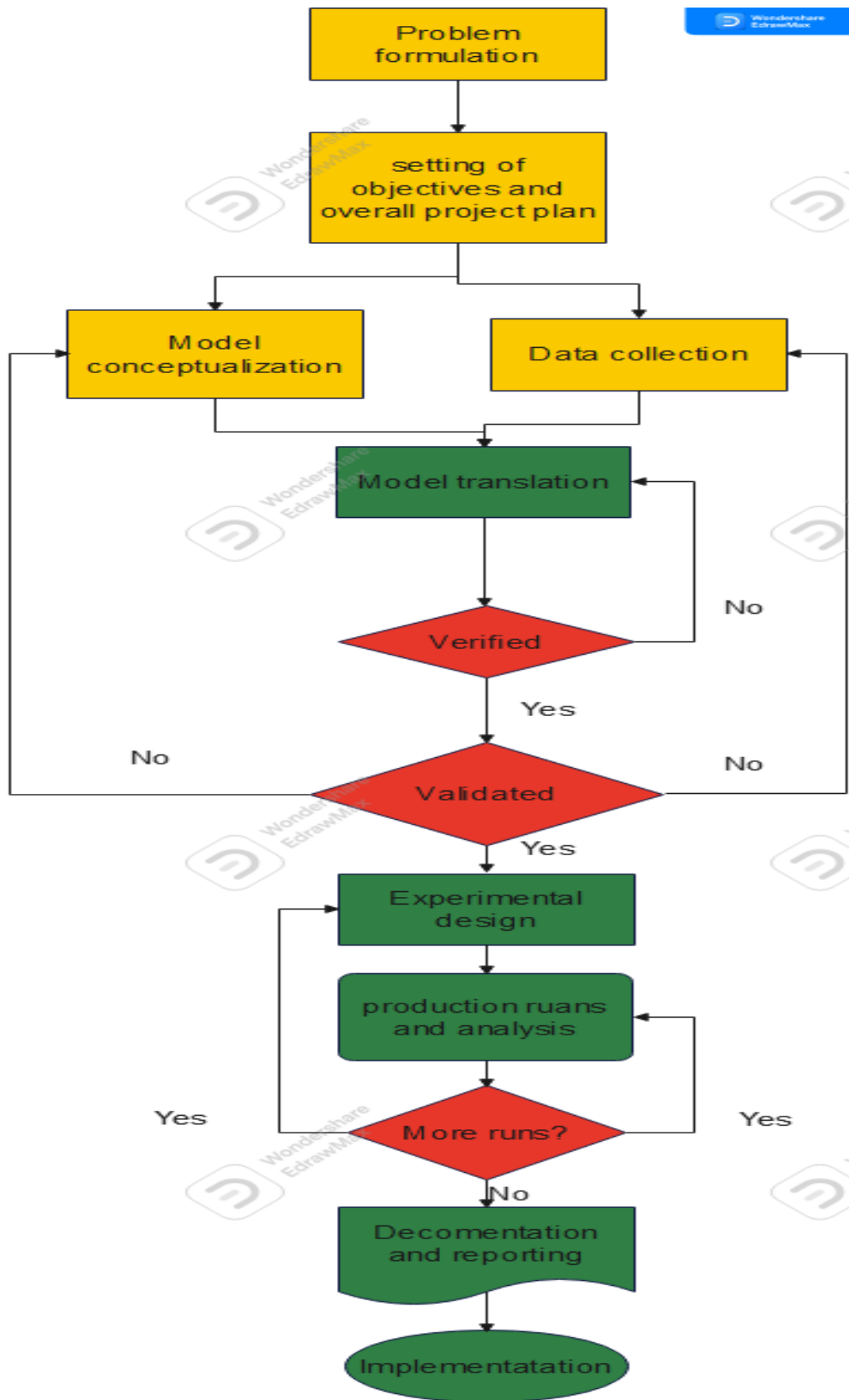


Figure 2.3: Steps in discrete event simulation building (Forcael et al., 2018)

2.4.1. Arena Simulation Software

Arena software enables you to bring the power of modeling and simulation to your business. It is designed for analyzing the impact of changes involving significant and redesigns associated with supply chain, manufacturing, processes, logistics, distribution, warehousing and service systems.

2.4.2. Arena Input Analyzer

Arena's Input Analyzer is a powerful tool that allows you to analyze different type of data; it is used to fit probability distributions to data and/or to evaluate the fit. Input Analyzer performs two goodness-of-fit tests for any distribution you attempt to fit: the chi squared test and the Kolmogorov-Smirnov test. For each test it prints the p-value, telling you how well the distribution fits your data(Ungureanu et al., 2005).

As it can be seen in Figure2.4, Input Analyzer also shows you how you would enter the distribution in an Arena simulation model; for example:WEIB(8.66, 2.78).

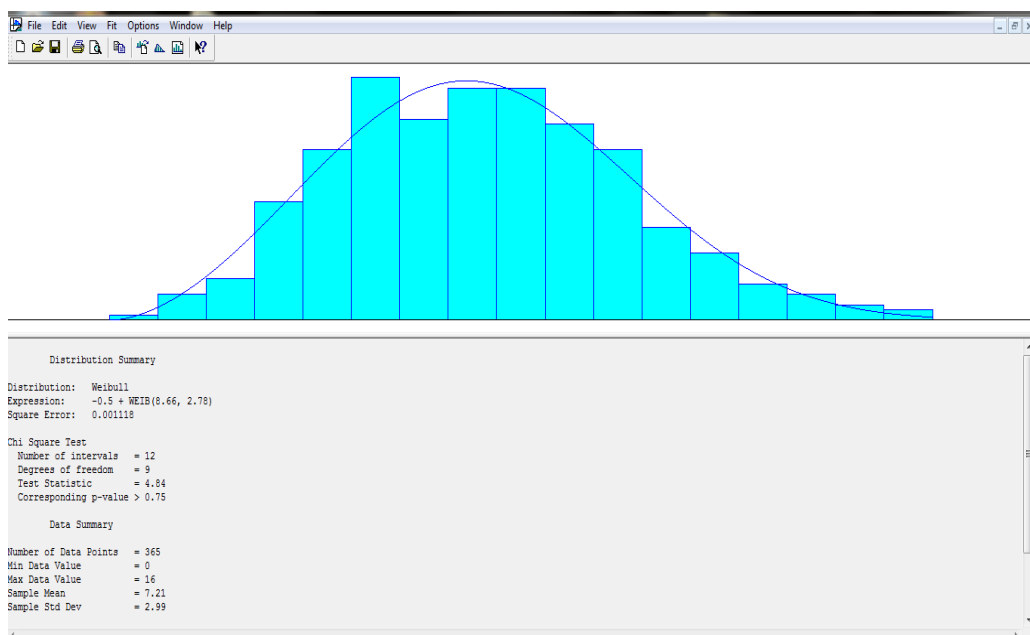


Figure 2.4: Arena Input Analyser

2.4.3. Arena Output Analyzer

Arena Output Analyzer is used for some of the plotting that it facilitates; its true usefulness is the ability to easily construct an auto-correlation plot and other kind of plots. An auto-correlation plot allows dependence in the data to be quickly examined. Creating Histograms, Process analyzer will give as results all the needed data to discuss, read and understand the plot. A Histogram Summary can be seen in Figure 2.5:

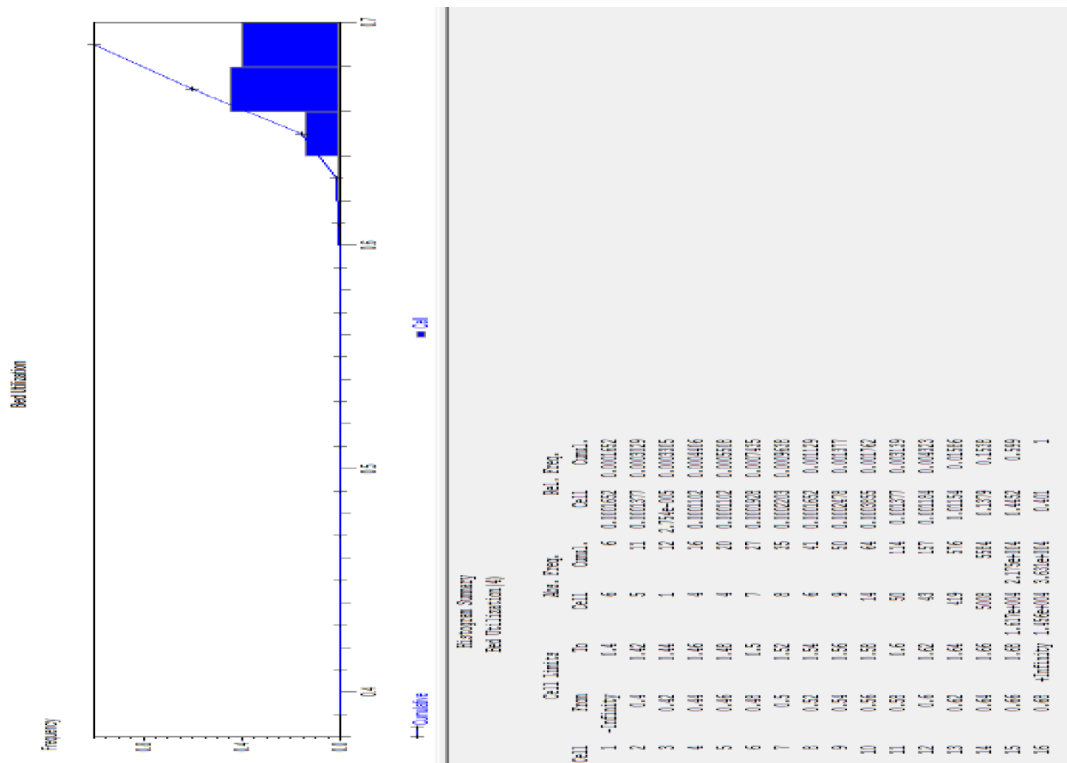


Figure 2.5: Arena output analyzer environment.

2.4.4. Arena Process Analyzer

The Arena Process Analyzer is a tool that supports parametric extraction of Arena models by allowing the modeler to create, run and compare simulates scenarios, and thus observe the effect of prescribed responses. The term parametric extraction refers to the activities of running a model multiple times with a different set of input parameters for each run, and then comparing the resultant performance measures. Its purpose is to understand the impact of parameters changes on system behavior (sensitivity extraction), often in the

process of seeking the optimal configuration (parameter set) with respect to one or more performance measures or combination thereof. In Process Analyzer input parameters are called controls, and the resultant performances values are called responses. Controls may consist of variables and resources capacities, while responses include both variables and statistics. In Figure2.6, the platform of Process Analyzer Environment is shown:

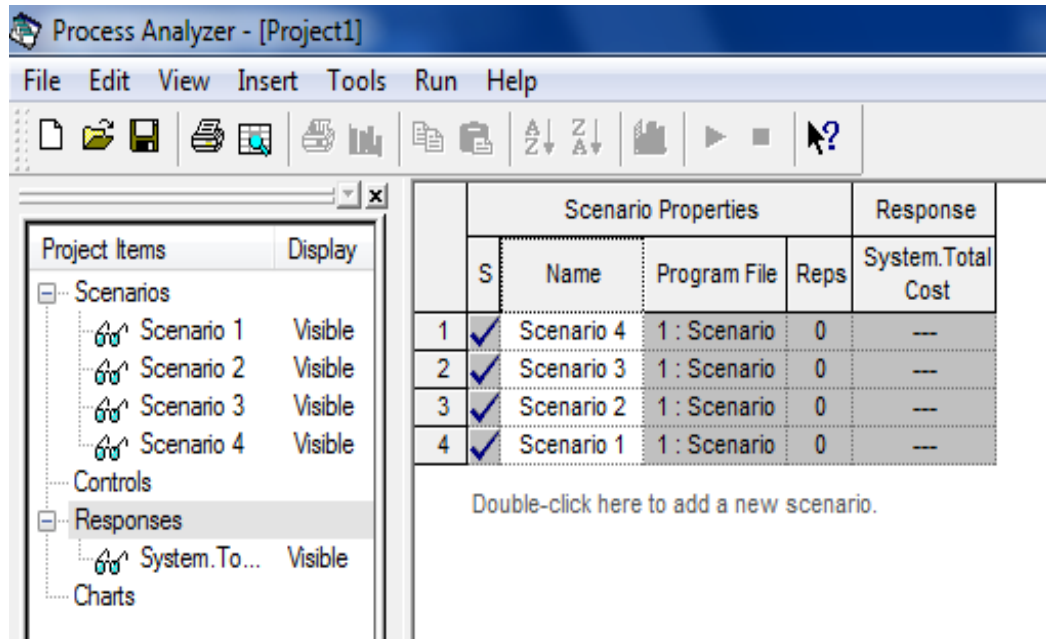


Figure 2.6: Arena Process Analyser.

2.4.5. Arena Opt Quest

OptQuest is one of the products developed by OptTek. An optimization software and services company, OptTek is the leading provider of optimization software to companies that employ simulation.(Laguna, 2011). Opt Quest overcomes this problem, automatically searching for the best solution within your Arena's model: "its ultimate goal is to find the solution that optimizes (maxims or minimizes) the value of the model's objective, and it's designed to find solutions that satisfy a wide variety of constraints that you may define". Figure 2.7 shows the platform of Opt Quest Arena simulation.

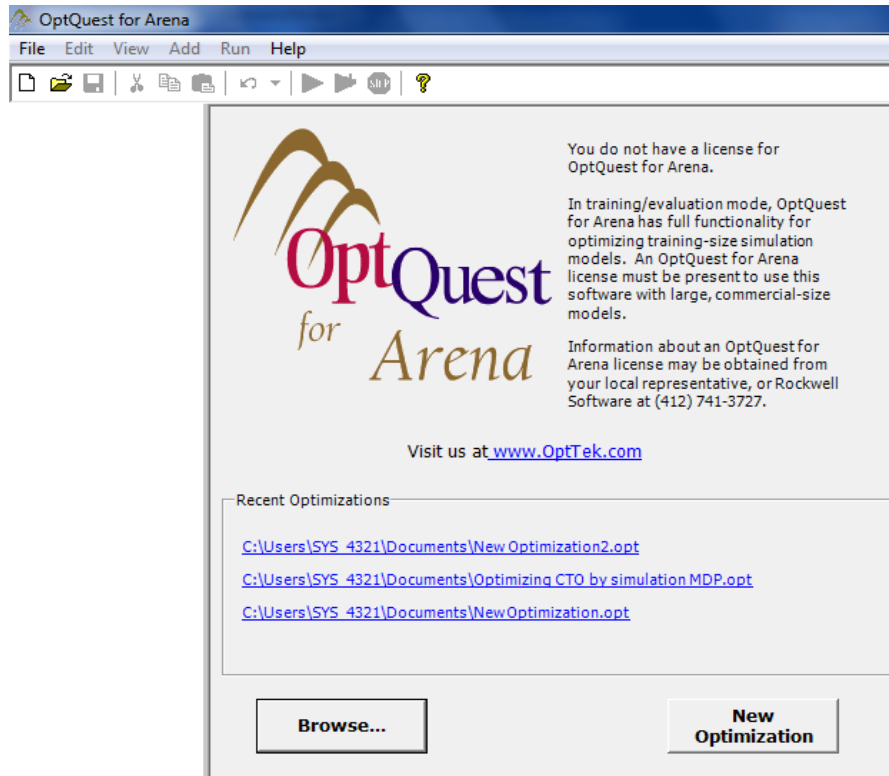


Figure 2.7: Opt Quest Arena Simulation

The optimization procedure uses the outputs from the simulation model to evaluate the inputs to the model; analyzing this evaluation and previous evaluations, the optimization procedure selects a new set of input values. The optimization is stopped when a criterion is satisfied; usually after a number of simulation or when the objective values stops to improve. Therefore, Opt Quest is an optimizer that makes it possible to separate successfully the optimization solution procedure from the simulation model.

2.5. Research gap identified

One of the issues, which have been neglected for many years in nation, is the dry port optimization via simulation in MDP CTO. A container terminal works under multiple operational objectives. Container terminal operations comprise of a very complicated set of container handling process. Container terminal operation in MDP is a system with several subsystems and a large number of decisions for each subsystem like: terminal operations at a terminal truck gate system, train side operations and yard side operations. As such, they

are unable to ensure optimal solution for container handling problems in container terminal. In this thesis, it is suggested that an optimization via simulation for solving container terminal operations to fill the gap.

The study employed an empirical research type to observe further and experiment the current status of container terminal operation. It was based on or characterized by recording and experiment instead of theory. A dry port container terminal can be considered as a queuing system defined basic parameters: truck/trains arrival rate and service rate, in an observed time unit. Appropriate indices of dry port container terminal operations are computed on the basis of these parameters. A model of cost as optimization assessed to run the dry port. Specifically, optimization using simulation is to examine the waiting line performance, to trade off cost of service and waiting, to assign optimal number of servers and to develop a working model for the container terminal operation

CHAPTER THREE

3. RESEARCH METHODOLOGY

3.1.Introduction

The study employed an empirical research type to observe further and experiment the current status of container terminal. It based on or characterized by recording and experiment instead of theory.

3.2.Research design

A research design is the arrangement of conditions for collection and extraction of data in a manner that aims to combine relevance to the research purpose with its economy in procedure. The research design is the conceptual structure within which research is conducted; it constitutes the blueprint for the collection, measurement and extraction of data. As such the design includes an outline of what the researcher will do from writing the research hypothesis/question and its operational implications to the final extraction of data (Stage & Manning, 2003).

A case study focuses on one occasion, but also takes into account the context in which it takes place, thus, including many variables (Johansson, 2007). This methodology was chosen because it allows in-depth study of a single object rather than a crowded sample. It enabled the researcher to consider the parameters that were studied and received detailed descriptions of those directly involved.

The main activity of a container terminal is the transfer of cargo units from one transport modality to another; auxiliary activities include the temporary storage of containers and value added services, such as cargo units maintenance and repair, and sometimes cargo

consolidation and deconsolidation activities, performed in dedicated areas known as Container Freight Stations. The standardization of containers allows goods to be handled quickly, safely and efficiently, using cranes, forklifts and reach stackers, to transfer cargo between different transport modalities, reducing transfer time and cost.

3.2.1. Area of study

The dry port is located in Oromia National Regional State Lome Woreda at Modjo town. The port occupies a total area of 150 hectare while 63 hectare land area is used for container terminal services. Modjo Dry Port is located 73 Km from the capital and it is connected to the new Ethio – Djibouti Rail way line. Figure 3.1 shows the physically ground of the port as follows:

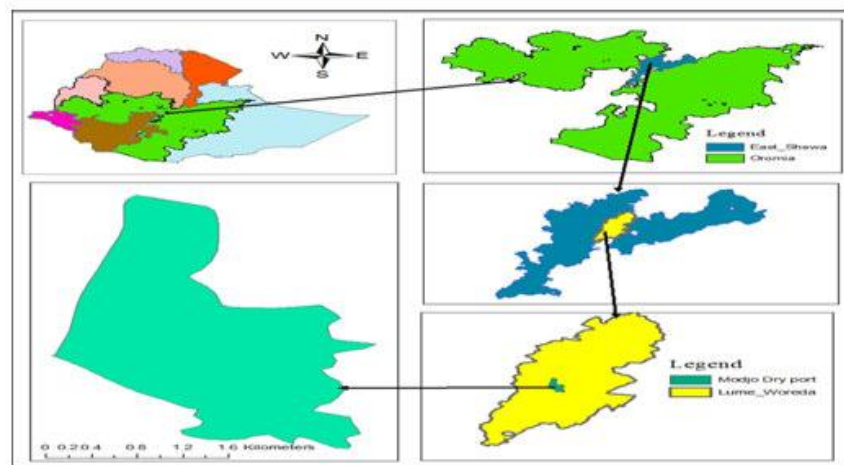


Figure 3.1: Location map of the current Modjo Dry Port (Ethio-GIS 2015)

3.2.2. The nature of data required

A discrete and continuous quantitative variable are only take specific numeric values and any value in an interval respectively; moreover those numeric values have a clear quantitative interpretation. Hence, the required data was discrete and continuous

quantitative variables which were number of arrivals, number of services provided and number of in and out trucks and trains.

3.2.3. Data collection sites

There were three main points of data collection. The first was at the gate of the truck. The gate had eight lanes for trucks for in and out. Four of them were dedicated for in trucks from outside and others four were dedicated for trucks out from MDP. Three lanes were serving for fully container trucks and one for empty trucks for in and out from MDP respectively. The second was at yard side and helped to collect cranes operations per hour and inter arrival of the trucks. The final one was at the train side and helped to collect trains inter arrival, checkup time in train side and crane service time.

Figure 3.2 shows the current of map of MDP CTO seen through Google Earth software.

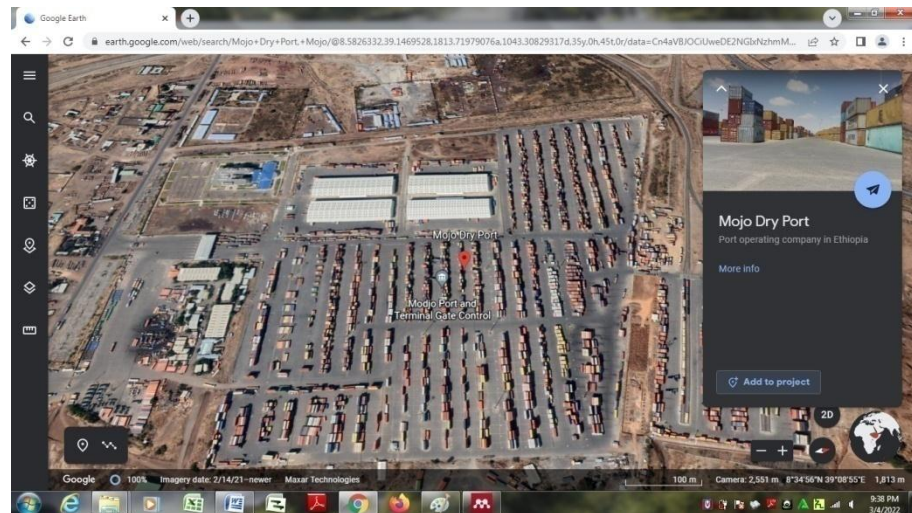


Figure 3.2: Current map of MDP CTO (source: Google Earth)

Figure 3.3 is the result of own sketching by looking at the dedicated areas of yard for different purposes. Each area is allocated to keep minimum distance from both gates of trains and trucks.

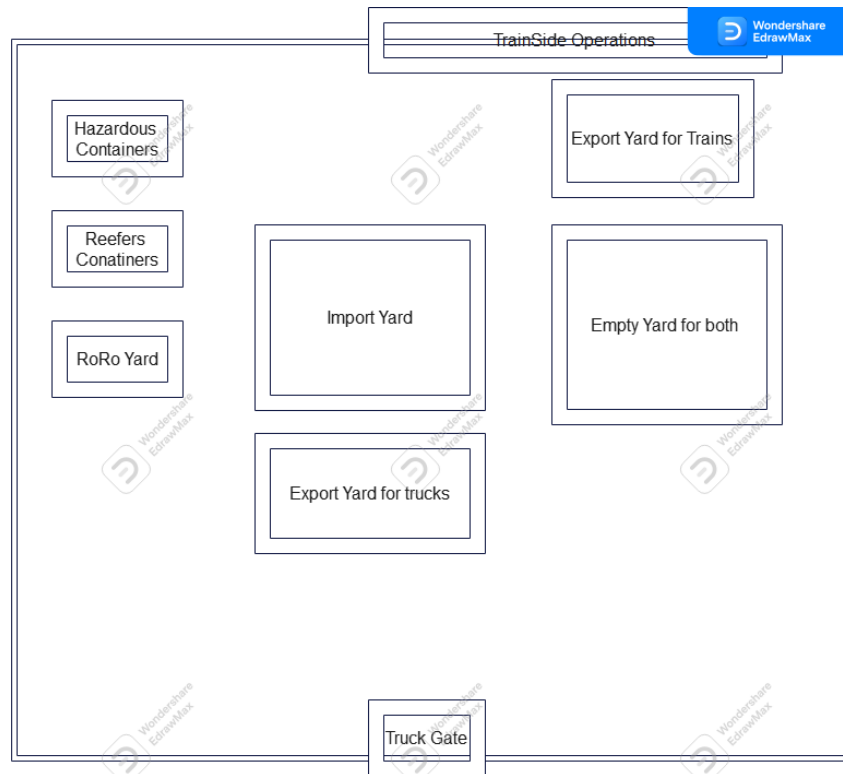


Figure 3.3: Layout of CTO in MDP (own drawing)

3.2.4. Study time

The research was carried out during the academic year of 2021/22 G.C. The study duration was of data collection starting from commencement of data collection till end including statistical extraction and reporting for six months. Specifically, the data collection consumed four weeks, 40 hours per week in September 2021.

3.2.5. Empirical research design

One of the principal goals of experimental design is to estimate how changes in input factors affect the results, or responses, of the experiment. One of the principal goals of experimental design is to estimate how changes in input factors affect the results, or responses, of the experiment. One of the principal goals of experimental design is to estimate how changes in input factors affect the results, or responses, of the experiment. One of the principal goals of experimental design is to estimate how changes in input factors affect the results, or responses, of the experiment

Empirical research draws from observed or measured phenomena and derives knowledge from actual experimentation or recording. It was designed to fit this requirement for the OvS for CTO.

3.3.Sampling design

Sample design helps to determine number of items to be included in the sample i.e., the size of the sample. Sample design is determined before data are collected. Researcher selected prepared a sample design which should be reliable and appropriate for research study (Madow, 1968)

3.3.1. Sampling

Sampling is used in practice for a variety of reasons such as: it can save time and money only when the population is infinite. However, when the universe (population) size is a small one, no need of sampling. The number of trucks and trains in/out of MDP is finite per day and year.

3.3.2. Steps in sampling design

There are four things should be defined clearly. The first is the universe or population. The population under study is all dedicated and eligible trucks and trains to transport containers from/to MDP. The second is sampling units. The sampling units are trucks and trains. The third is Source list. The source list included all dedicated and eligible trucks and trains from/to MDP. Finally, Size of sample is taken according to Carvalho (1984), sample size can be determined as follows:

Table 3.1: Carvalho's sample size Table

Population	Sample Size		
	Small	Medium	Large
51-90	5	13	20
91-150	8	20	32
151-280	13	32	50
281-500	20	50	80
501-1200	32	80	125
1201-3200	50	125	200
3201-10,000	80	200	315
10,001-35,000	125	315	500
35,001-150,000	200	500	800

3.3.3. Sampling method or procedure

It made all possible attempts to save the cost of collecting raw data and the cost of incorrect inference resulting from the data (systematic bias and sampling error).

3.3.4. Criteria of selecting a sampling procedure

Generally, two costs are involved in a sampling extraction, which govern the selection of sampling procedure: the cost of collecting the data—it increases as sample size becomes larger and larger and the cost of an incorrect inference resulting from the data—here are two causes of incorrect inferences, which are Systematic bias/error and Sampling error .

3.3.5. Type of sampling design

Non-probability sampling was considered desirable for the universe found small and a known characteristic of it studied intensively.

3.4.Data collection methods

The method in the data collection was a direct recording and documents of MDP were examined thoroughly. The collected data were inter-arrival time, inter-service time, and unit cost of service by server and cost of waiting by customer at Modjo Dry Port up to steady state.

3.4.1. Time measurement

Under this method, the information is sought by way of investigator's own direct recording and recording the existing situations without asking from the respondent. Structured recording was conducted to get appropriate inputs for descriptive studies. The researcher simply observed the activities without taking part himself what is called non-participant recording.

3.4.2. Simulation methods

Some problem situations are too and dynamic in nature to be represented by the concise analytical models and techniques. Simulation involves the construction of an artificial environment within which relevant information and data can be generated (Sargent, 2011).

- Simulation models have an expected rather than an absolute behavior, and may have widely differing results depending on configuration and input data.
- The kind of testing used in development of software systems is used to get a simulation model in functional order, but additional testing is required for verification and validation of the simulation model.

- Validation is the task of determining if the model constructed accurately represents the underlying real system being modeled. For any simulation model that is to be used in actual application it is very important to validate the model insofar as practicable, since real decisions are going to be made based on the simulation outcomes.
- Because a simulation model provides a surface “realism”, it is possible to be fooled by the realistic appearance of the simulation. The best defense against this kind of mistake is to employ multiple means of comparing model performance against real data (if available), including statistical testing.
- In model construction, involve people with domain knowledge, particularly for developing the model elements. Domain experts should also have expert knowledge on where and what input/output data to incorporate. There may be previous work (such as lab experiments) or statistical models from which some model elements can be extracted or developed.

3.4.3. Document extraction

Document extraction is useful for understanding policy content across time and geographies, documenting processes, triangulating with other sources of data, understanding how information and ideas are presented formally, and understanding issue framing, among other purposes. Hence, published and unpublished document at the MDP, were investigated thoroughly to get the current and past performances of the company and even future plan of expansion.

3.5.Data analysis and interpretations

Most of real-world problems can be analyzed by applying a specific type of technique and then performing the optimization via simulation. Simulation is highest form of extraction. To simulate the queuing system, it is possible to use available simulation software to tackle operations systems in container terminal operation in Modjo Dry Port. Arena input analyzer, output analyzer; PAN analyzer and Opt Quest were employed per required for the examination of system (Ungureanu et al., 2005).

3.6.Flow Chart of the model

The following activity diagram of MDP CTO @train side begins with arrival of trains, follows by checkup process, then loading/unloading operations and finally the departure of the train as independent entity. The flow chart in Figure 3.4 expresses clearly as follows:

- **Arrival trains:** this represents the arrival of successive trains in for operations.
- **Check-in/out train:** the dedicated inspection team inspects the documents of carriage for 106TEU and lets the train for next queue process.
- **Queue train in:** the first train comes in served first per regulation of MDP.
- **Unloading train:** the decision whether the train drops off empty containers (EC) or full containers (FC)
- **Unloading FC:** the operation is unloading the train with full containers.
- **Unloading EC:** the operation is unloading the train with empty containers.
- **Loading train:** the decision whether the train load empty containers (EC) or full containers (FC)
- **Loading FC:** the dedicated cranes load the train with full containers.
- **Loading EC:** the dedicated cranes load the train with empty containers.

- **Queue train out:** the trains be in line for checkup process to be out.
- **Check out Train:** the dedicated inspection team inspects the documents of carriage for 106TEU and lets the train for departure event.
- **Departure of Trains:** the train leaves the MDP after the accomplishment of the operations like loading/unloading FC or EC.

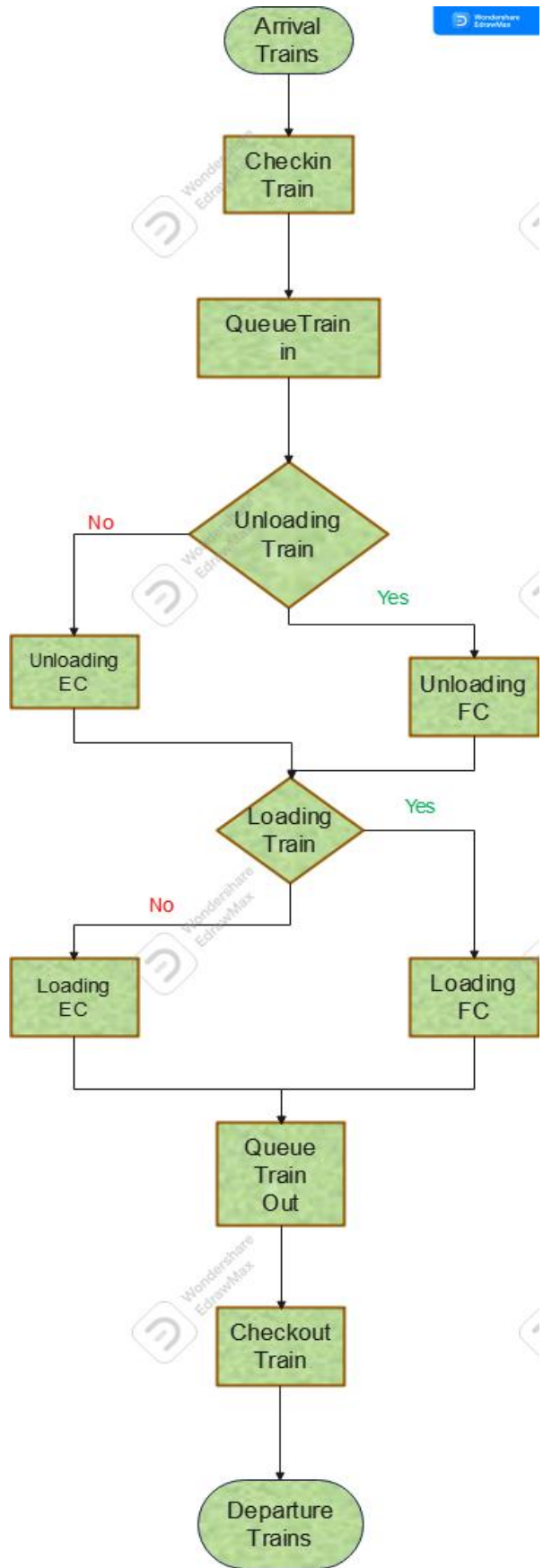


Figure 3.4: Activity diagram of MDP CTO @train side

The following activity diagram of MDP CTO @truck side begins with arrival of truck follows by checkup process, then loading/unloading operations and finally the departure of the truck as independent entity. The flow chart in Figure3.5 expresses clearly as follows:

- **Arrival trucks:** this represents the arrival of successive trucks in for operations as an independent entity.
- **Trucks (decision):** the decision is about whether the truck with empty or full container.
- **Check in truck EC:** the dedicated inspection inspects the truck with empty containers against the presented carriage documents.
- **Check in truck FC:** the dedicated inspection inspects the truck full containers against the presented carriage documents.
- **Queue truck YD:** the queue yard operation for loading empty or full containers
- **Loading (decision):** the dedicated crane load a truck with empty or full containers against the carriage document presented.
- **Unloading (decision):**the dedicated crane drop off a truck with empty or full containers against the carriage document presented.

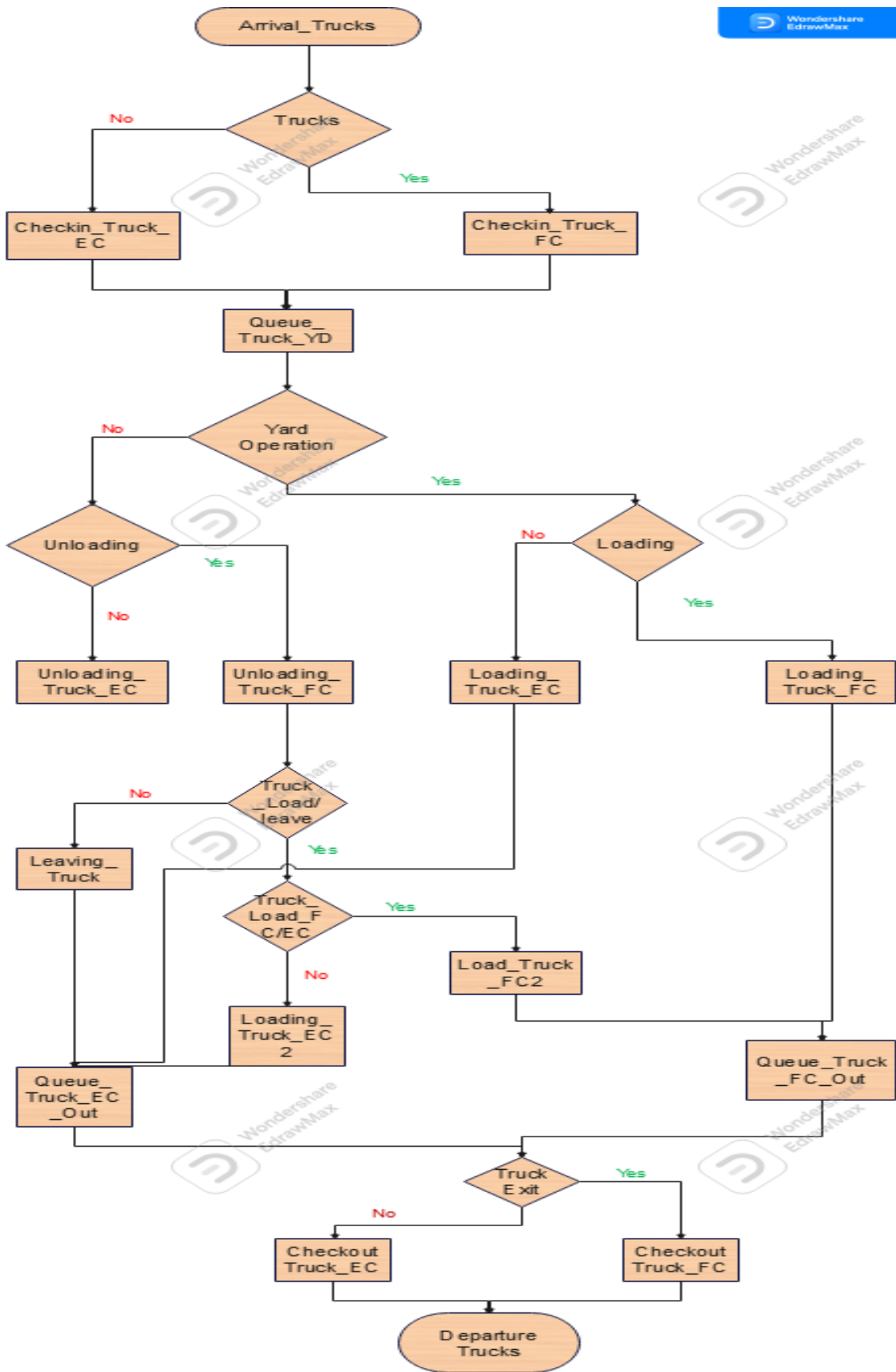


Figure 3.5: Activity diagram of MDP CTO @ truck side

3.7. Comparison of current practices with new suggestion

The following flow chart helps us to compare the real system against the developed simulation model. Figure 3.6 shows the simulated system imitates operation of actual system over time ,artificial history of system can be generated and observed , internal (perhaps unobservable) behavior of system can be studied , time scale can be altered as needed. Conclusions about actual system characteristics can be inferred in Figure3.6, actual system (real system) is compared with simulation.

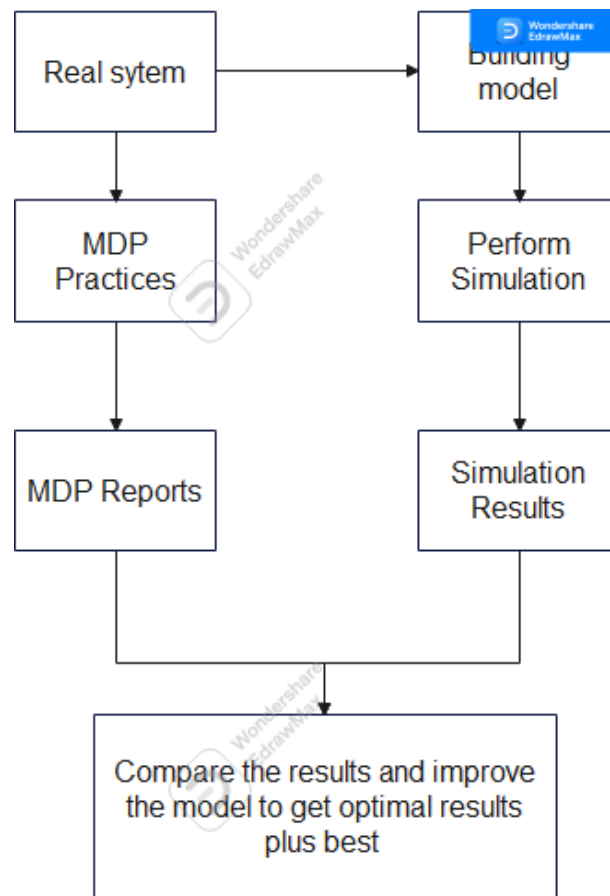


Figure 3.6: Comparing Real vs. simulation flow chart (own sketching)

CHAPTER FOUR

4. ANALYSIS OF DATA AND INTERPRETATIONS

4.1. Introduction

For a proper modeling of the system, efficiency in data collection and statistical processing phase is considered essential. Depending on the circumstances, an attempt was made to obtain system data from three main sources. The sources are gate operation of truck, yard operation and train side operation. Basically, the data used for this study were obtained from primary sources. The method of data collection was through direct recording, document extraction and simulation.

Stochastic systems in MDP have one or more random characteristics that affect the system. Starting from the methods already mentioned for the inputs of this system. The researcher interested in analyzing the time between arrivals of entities, the time of different processes, different deadlines. Most simulation data have an implicit delay time, such as the time between arrivals; check times, etc., and for other data, a probability part, and then we can get a definition of system history data.

Model inputs can be constants, but are typically random variables. Input models can have a significant impact on model outputs and conclusions one draws from models. Outputs are a result of inputs of simulation models. Inputs are typically collected and modeled by observing the real system and also talking with “experts” at MDP (Yin & McKay, 2018).

Figure 4.1 shows the input-output process model for the simulation model. Input data provide the driving force for a simulation model. The model logic shows the extraction mechanism can used to give an output. The model outputs represent the result of input and the model logic mechanism to give an ultimate output.

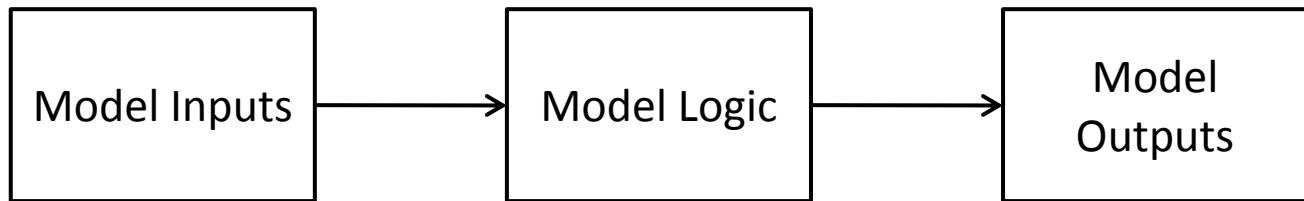


Figure 4.1: Input-output process of model (Nguyen & Pomona, 2014)

There are four steps in the development of a useful simulation model:

- I. Collect input data from the real system
- II. Identify a probability distribution to represent the input process
- III. Choose parameters for the distribution
- IV. Evaluate the chosen distribution and parameters for goodness of fit.

4.2. Data Collection

All data collected from direct recording of the researcher at three collection sites of MDP CTO, documents of MDP from planning office and own construction of artificial data after talking to “experts” in MDP (Yin & McKay, 2018).

4.2.1. Time measurement

The sample recording listed here under in Table 4.1 shows the inter arrival of successive trains to train side operations was taken in September 2021. There were 72 round trips of trains in that month. The time was measured using stopwatch by the researcher himself and daily activities recorders of the MDP. The train can be with empty or full containers and any form of containers to the dry port. The values of the data are maximum value of 551 minutes, minimum value of 31, sample mean of 159 and sample of standard deviation of 126.

Table 4.1: Inter arrival of successive trains to train side operations

Trains	Minutes	Trains	Minutes	Trains	Minutes	Trains	Minutes	Trains	Minutes	Trains	Minutes
1	44	15	71	29	164	43	60	57	213	71	105
2	46	16	60	30	415	44	153	58	31	72	91
3	86	17	87	31	551	45	396	59	143		
4	49	18	101	32	194	46	183	60	115		
5	63	19	99	33	126	47	401	61	146		
6	534	20	81	34	386	48	72	62	247		
7	141	21	178	35	108	49	409	63	72		
8	341	22	251	36	120	50	89	64	32		
9	221	23	84	37	401	51	60	65	139		
10	73	24	57	38	72	52	153	66	40		
11	406	25	87	39	409	53	396	67	39		
12	49	26	230	40	89	54	183	68	50		
13	90	27	39	41	133	55	272	69	250		
14	162	28	115	42	165	56	139	70	397		

The second sample recording listed here under in Table 4.2 shows the inter arrival of successive trucks to gate operations was taken in September 2021. There were 170 round trips of trucks in that month. The time was measured using stopwatch by the researcher himself and daily activities recorders of the MDP. The truck can be with empty or full containers and any form of containers to the dry port. The values of the data are maximum value of 19 minutes, minimum value of 0, sample mean of 4.44 and sample of standard deviation of 3.99.

Table 4.2: Inter arrival of successive trucks to gate operations

Trucks	Minutes	Trucks	Minutes	Trucks	Minutes	Trucks	Minutes	Trucks	Minutes	Trucks	Minutes
1	0	31	7	61	2	91	2	121	0	151	1
2	5	32	4	62	4	92	4	122	5	152	3
3	4	33	2	63	1	93	8	123	2	153	8
4	4	34	8	64	3	94	1	124	3	154	2
5	2	35	10	65	3	95	6	125	4	155	2
6	5	36	3	66	1	96	4	126	2	156	1
7	16	37	1	67	4	97	5	127	1	157	12
8	9	38	9	68	7	98	6	128	4	158	0
9	6	39	3	69	4	99	3	129	15	159	2
10	11	40	1	70	1	100	2	130	1	160	2
11	7	41	8	71	1	101	2	131	3	161	1
12	6	42	0	72	3	102	4	132	2	162	5
13	2	43	2	73	2	103	9	133	14	163	1
14	4	44	2	74	9	104	2	134	10	164	3
15	3	45	1	75	2	105	5	135	1	165	7
16	0	46	4	76	1	106	1	136	2	166	5
17	2	47	6	77	2	107	1	137	1	167	6
18	9	48	6	78	5	108	5	138	6	168	0
19	0	49	0	79	4	109	8	139	15	169	4
20	5	50	2	80	0	110	4	140	3	170	2
21	17	51	0	81	1	111	19	141	2		
22	9	52	6	82	3	112	0	142	1		
23	10	53	6	83	12	113	5	143	13		
24	10	54	0	84	2	114	14	144	6		
25	13	55	5	85	2	115	3	145	0		
26	2	56	3	86	1	116	0	146	12		
27	9	57	7	87	7	117	4	147	13		
28	1	58	1	88	1	118	1	148	3		
29	4	59	0	89	9	119	0	149	6		
30	13	60	1	90	3	120	8	150	5		

4.2.2. Document extraction

The following summarized Table 4.3 drawn from the planning office of MDP contained reefers, hazardous, RoRo and consolidated containers. The Table contains the full transaction of the September, 2021; it was a time of study in MDP. The fragmented data collected and tabulated per demand of the researcher to triangulate with recording and simulation values.

Table 4.3: Yard blocks transactions

Containers	TEU/month	Remark
Full in	9528	The containers can be any of reefers, hazardous, RoRo and consolidated transported by trucks and trains.
Full out	9052	
Empty in	8021	
Empty out	8227	

Table 4.4 shows the collected data for round trips of trucks and trains in summarized way. The containers were transported by trucks and trains. The containers transported of both empty and full containers for the month of September, 2021 was 17,412 TEU/month.

Table 4.4: Number of containers transported by truck or trains

Transported by	Train/ Truck	Remark
Round trip of train with FC in month	50	$50 \times 106 = 5,300$ TEU/month
Round trip of trains with EC in month	22	$22 \times 106 = 2,332$ TEU/month
Round trip of trucks with FC/EC in month	163	$163 \times 2 \times 30 = 9,780$ TEU/month
Total containers transported		17,412 TEU/month

The general parameters were collected from the document of MDP which discuss about their daily operations, rules, capacity of train & trucks and working space & time. These data values are extracted from MDP documents and their regulation so that to fit the objectives of the study. Table 4.5 shows the general parameters which are helpful and can be used wherever necessary in the simulation model.

Table 4.5: General parameters

General parameters	Quantity	Units
working days	365 days/year	days/year
Working hours	12	8:00A.M-8:00P.M
A truck has a capacity of	2	TEU
A train has a capacity of	106	TEU
Terminal area	630,000	m ²
Average container dwell time	12	days
Container free from cost for up to x days	15	days

4.2.3. Statistically input distributions

The statistically input distributions drew from the inputs of raw data from truck side operations using Arena simulation software package. Table 8 shows the input distribution data for modeling CTO in MDP. The truck is one of its system entities in modeling. All the mathematical expressions used in their respective positions in simulation model. The raw data is fed and the possible distributions are produced as follows in Table 4.6:

Table 4.6: Statistically input distributions chosen for truck side

Operations at truck side	sample size	Distribution-in minutes	Explanations
Inter arrival of trucks to gate	170	EXP(4)	The average round-trip of trucks per day was 170 and all sample points were taken on arrival day. See Table 4.1.
Check in/out time at gate	170	TRIA(3,5,8)	The average round-trip of trucks per day was 170 and all sample points were taken on arrival day. See Table 7.1.
Heavy duty cranes time takes to load/unload a truck with FC.	90	TRIA(5,10,15)	The average round-trip of trucks per day was 90 with FC and all sample points were taken on arrival day. See appendix VII.
Light duty cranes time takes to load/unload a truck with EC.	80	TRIA(5,10,15)	The average round-trip of trucks per day was 80 with EC and all sample points were taken on arrival day. See appendix IX.
Queue at yard operations with their inter arrival	170	EXP(4)	The average round-trip of trucks per day was 170 and all sample points were taken on arrival day. See appendix V.

The statistically input distributions drew from the inputs of raw data from train side operations using Arena simulation software package. The raw data is fed and the possible distributions are produced as shown in Table 4.7. Table 4.7 shows the input distribution data for modeling CTO in MDP. The train is one of its system entities in modeling. All the mathematical expressions used in their respective positions in simulation mode.

Table 4.7: Statistically input distributions chosen for train side

Operations at train side	sample size	Distribution- in minutes	Explanations
Inter arrival of trains	72	EXP(120)	The average round-trip of trains per month was 72 in September 2021 and all sample points were taken. See appendix II.
Check in/out at train side	72	TRIA(30,45,60)	The average round-trip of trucks per month was 72 in September 2021 and all sample points were taken. See appendix IV.
Heavy duty cranes time takes to load/unload a train with FC	38	TRIA(64,94.6,114)	The average round-trip of trucks per month was 38 in September 2021 and all sample points were taken. See appendix VIII.
Light duty cranes time takes to load/unload a train with EC	34	TRIA(73,92.4,123)	The average round-trip of trucks per month was 38 in September 2021 and all sample points were taken. See appendix X.
Queue with inter arrival of time in minutes	72	EXP(100)	The average round-trip of trucks per month was 72 in September 2021 and all sample points were taken. See appendix VI.

4.3. Statistical extraction of output from terminating simulations

Output extraction is the examination of the data generated by a simulation. Its purpose is either to predict the performance of a system or to compare the performance of two or more alternate system designs. The need for statistical output extraction is based on the recording that the output data from a simulation exhibits random variability.

4.3.1. Time frame of simulations

- Runs for some duration of time T_E , where E is a specified event that stops the simulation. There are twelve hours operations at MDP per day.
- Starts at time 0 under well-specified initial conditions. The operations begin at 8:00 A.M.
- Ends at the stopping time T_E . The ends at 8:00 P.M.
- The simulation analyst chooses to consider it a terminating system because the object of interest is one day's operation.

4.3.2. Strategy for data collection and extraction

- For terminating case, make IID replications
- Run>Setup>Replication Parameters: Number of Replications field and make the first 10 replication for trial and error.
- Check both boxes for Initialize Between Replications
- Separate results for each replication – Category by Replication report.

The replication Table obtained from the first ten sample run of the simulations, the Table 4.8 was useful for the subsequent processing and in calculating confidence intervals and the results summarized using Table 4.8 as follows:

Table 4.8: Table of replication by category

Replication	Total cost
1	1,492,384.82
2	1,285,699.12
3	1,538,018.01
4	1,298,845.64
5	1,344,037.21
6	1,473,125.34
7	1,273,373.48
8	1,321,295.37
9	1,499,559.34
10	1,476,387.64

4.3.3. Confidence intervals

A confidence interval displays the probability that a parameter will fall between a pair of values around the mean. Confidence intervals measure the degree of uncertainty or certainty in a sampling method. They are most often constructed using confidence levels of 95% or 99%.

Strictly speaking a 95% confidence interval means that if we were to take 100 different samples and compute a 95% confidence interval for each sample, then approximately 95 of the 100 confidence intervals will contain the true mean value (μ).

Viewing the cross-replication summary outputs as the basic data and this information (except standard deviation) is in Category Overview report of Arena simulation.

The following table obtained using Table 4.8 as an input. Table 4.9 shows the new number of replications is 100 after taking the first10 replications of Table 10 in to calculation to get

the half width $\pm 20,500$ or less. This keeps the percentage of rejection less than or equal to 5%.

Table 4.9: Table of number of replications calculations

Extraction of 10 replications		Remark	
Sample mean	1,400,272.60		
Sample standard deviation	103,995.22		
95% confidence interval half width	70,016.63		
Minimum summary output value	1,273,373.48		
Maximum summary output value	1,538,018.01		
Calculating the following parameters based on the above results			
Confidence interval	1,400,272.60 \pm 70,016.63	$\bar{x} \pm z_{n-1, 1-\alpha/2} \frac{s}{\sqrt{n}}$	
confidence interval	95%	Percent of rejection $\leq 5\%$	
Half width	70,016.63	$z_{n-1, 1-\alpha/2} \frac{s}{\sqrt{n}}$	s=standard deviation n=number of replications
Number of replications	≈ 100	$n_{new} = Z^2_{1-\alpha/2} \frac{s^2}{h^2}$	h=set half width , Let's get this down to $\pm 20,500$ or less which is half width

4.4.Final results MDP CTO simulation model

After the simulation comes to an end, Arena automatically shows all the significant results concerning the model's performances. Those are presented in the current section, divided into three categories, regarding the number of entities in/out/WIP, Queue situation and resources.

4.4.1. KPIs regarding the number of entities in/out/WIP

The key performance indicators of entities (trucks and trains) are illustrated using descriptive statistics in Table 4.10. The Table gives details of number in, number out and work in process of entities.

Table 4.10: The descriptive statistics of trains and trucks to MDP CTO per day

Number in	Average	Half Width	Minimum Average	Maximum Average
Trains	5.6100	0.16	2.0000	6.0000
Trucks	182.98	2.32	144.00	200.00
Number out	Average	Half Width	Minimum Average	Maximum Average
Trains	2.7100	0.21	1.0000	5.0000
Trucks	168.60	2.23	136.00	196.00
WIP	Average	Half Width	Minimum Average	Maximum Average
Trains	3.0526	0.16	1.1343	4.8955
Trucks	12.8950	0.35	8.3773	17.5427

4.4.2. KPIs regarding the Queue situation at the system's processes

Table 4.11 shows 16 queue stations with their time of waiting. The trains have higher queue of delay time to check in and unloading EC and FC. The queue situation expresses the number of trucks or trains which are looking for service in the MDP. The queue varies per capacity of each station as shown Table 4.11:

Table 4.11: Waiting time at each queue station

Waiting Time in minutes	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Checkin_Train_Queue	11.3111	2.56	0	61.1529	0	152.78
Checkin_Truck_EC_Queue	4.1915	0.34	1.449	13.9442	0	56.6986
Checkin_Truck_FC_Queue	6.7823	0.58	1.7846	16.9597	0	62.501
CheckOut_Train.Queue	3.5739	1.16	0	26.9247	0	68.3078
CheckOut_Truck_EC_Queue	2.8291	0.33	1.1483	14.0476	0	40.5572
CheckOut_Truck_FC_Queue	4.5997	0.47	1.4643	15.6663	0	50.8527
Load_EC_TrainQueue	4.82	2.38	0	69.7006	0	144.78
Load_FC_TrainQueue	6.9365	2.8	0	73.171	0	139.74
Loading_Truck_EC1.Queue	6.3322	0.86	1.2723	29.8903	0	85.6408
Loading_Truck_EC2.Queue	3.3785	0.35	0.6804	10.9019	0	42.6863
Loading_Truck_FC1.Queue	9.9222	1.19	2.3134	43.6766	0	124.93
Loading_Truck_FC2.Queue	5.0239	0.66	0.5349	20.7557	0	57.8365
Unload_EC_TrainQueue	10.3704	4.39	0	109.55	0	245.12
Unload_FC_TrainQueue	10.4054	3.52	0	82.4699	0	177.18
Unloading_Truck_EC.Queue	5.4076	0.62	1.4833	18.8086	0	61.752
Unloading_Truck_FC.Queue	6.7126	0.71	1.55	20.2126	0	58.6893

4.4.3. KPIs regarding the system's resources

Figure 4.2 shows key performance indications of resources consumption in MDP. The usage cost combined with busy cost is about 81% which is a good performance in resources consumptions. The idle cost is less than 20% which need more attention to be minimized in respecting the optimality curve. The resources consumption by entities in the MDP as shown Figure 4.2:

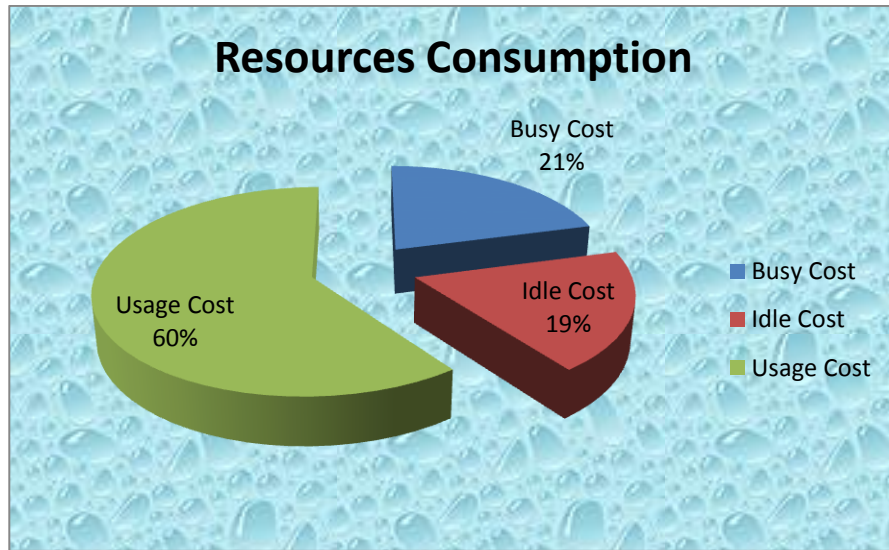


Figure 4.2: Resources consumption in MDP

4.5. Comparing many scenarios via the Arena Process Analyzer (PAN)

Normal working hours are 8 hours a day or 48 hours a week (Article 61). They should be distributed evenly, but may be even calculated over a longer period of time (Articles 63 and 64). Workers are entitled to a weekly rest period of 24 non-interrupted hours in a period of 7 days. Unless otherwise stated in a collective agreement, the weekly rest should be on Sunday, but another day may be chosen for certain services (Article 70). Overtime work is limited to two hours per day, 20 hours a month or 100 hours annually. Overtime is paid at 125% of the basic wage but can be more depending on when the overtime is worked. Weekend overtime is paid at double the standard rate and at 250% on a public holiday (Gazette, 2019).

The model's behaviors under these circumstances were analyzed and additional suggestions are consequently made. It also based on system number out and system total cost. The scenarios are explicitly:

Scenario 1: CTO works for 6 hours a day and 365 days a year.

Scenario 2: CTO works for 12 hours a day and 365 days a year.

Scenario 3: CTO works for 18 hours a day and 365 days a year.

Scenario 4: CTO works for 24 hours a day and 365 days a year.

Figure 4.3 show the output of the four scenarios taking system total cost and system number out as response and keeping all resources as controls for all scenarios. As seen in the Figure 4.3 all scenarios are based on the working times which are divided into 6 hours, 12 hours, 18 hours and 24 hours of working.

Scenario Properties				Responses	
S	Name	Program File	Reps	System.NumberOut	System.Total Cost
1	Scenario 1	1 : Scenario1	100	78.710	645255.082
2	Scenario 2	1 : Scenario2	100	171.310	1435050.673
3	Scenario 3	1 : Scenario3	100	205.150	1863252.046
4	Scenario 4	1 : Scenario4	100	205.790	2066073.740

Figure 4.3: Scenario extraction by total cost of the system and total number out

The two extremes are scenario1 and scenario2 with their respective advantage. However, the average current system number out is about 170 with cost of about 1.6 million. Here we can maximize the system number out up to 205 by cost of 1.8 million which is scenario3 which is better than scenario2, do not meet the peak time and future demand. Hence, the scenario3 ranked 1st per recording of the researcher seen from the Figure 4.4 and 18. It is a scenario of working 18 hours with given resources 18 hours a day, 7 days a week and 365 days a year. This actually decreases overall cost of MDP CTO and increase system number out which meets the peak day and immediate future demands of the container terminal operations.

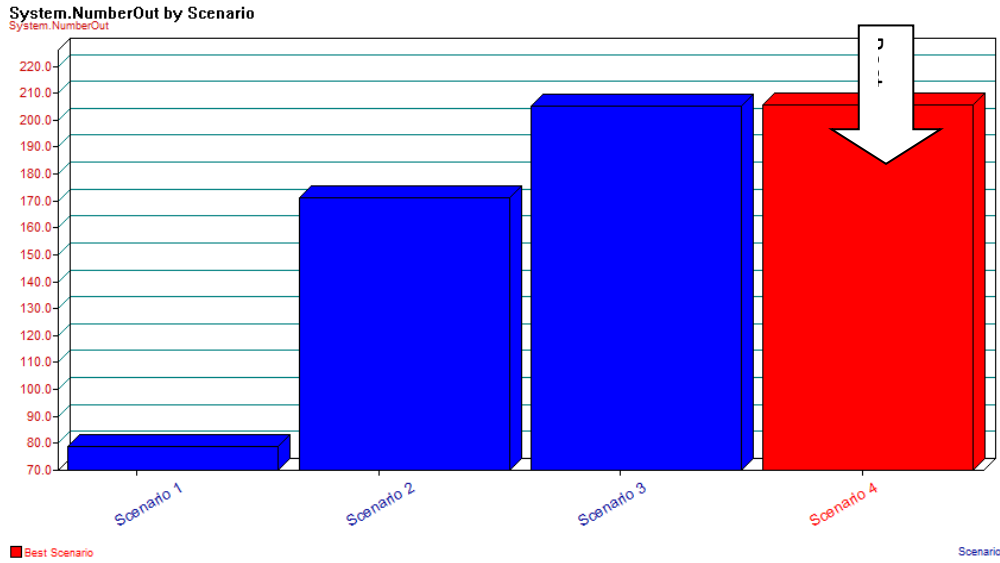


Figure 4.4: Scenario analysis based on system number out

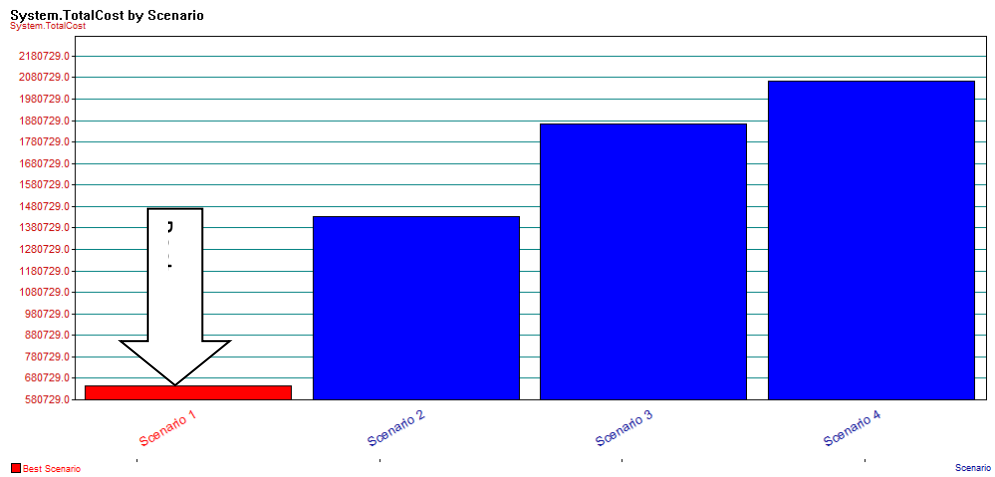


Figure 4.5: Scenario analysis based on system total cost

4.6. Searching for an optimal solution with Opt Quest

Formulate as an optimization problem:

Minimize: Total Cos of CTO

Name	Description
New Objective	
Expression	[System.TotalCost]
<input type="radio"/> Maximize <input checked="" type="radio"/> Minimize	
<input type="button" value="Check Expression"/>	

Subject to:

- I. $5 \leq \text{Sum of light duty cranes} \leq 10$
- II. $5 \leq \text{Sum of heavy duty cranes} \leq 10$
- III. $6 \leq \text{Sum of Inspection team} \leq 12$

After running the first 100 simulations, the result came down to the best value as seen in Figure 4.6.

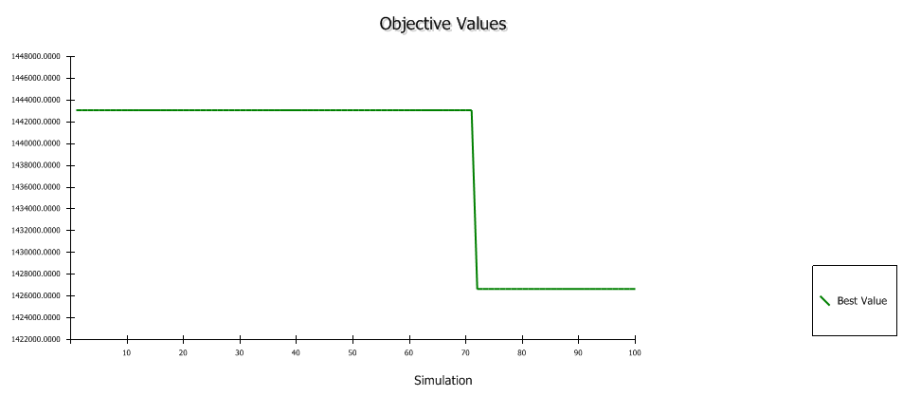


Figure 4.6: Best solution for the first 100 simulations

The following Table 4.12 carried the optimal solution for MDP CTO and summarized in the Table per quantity of each resource per day operations. The Table is taken among others and the best one after running the first 100 simulations. The Table 4.12 shows the optimal solution for the first 100 simulations was found to be ETB 1,426,646.55 per day operations in the system. This cost includes servers like light or heavy duty cranes in both gate (Truck and train), inspection team and plus waiting cost of entities.

Table 4.12: Table optimal solution for current MDP CTO

NEW BEST SOLUTION	
Decision Variables	Values of variables
Heavy_1_Duty_Crane_@_TrainSide:	1
Heavy_2_Duty_Crane_@_TrainSide:	1
Heavy_Duty_Crane_1_@_TruckSide:	1
Heavy_Duty_Crane_2_@_TruckSide:	1
Heavy_Duty_Crane_3_@_TruckSide:	1
Inspection_Team_1_@_TrainSide:	1
Inspection_Team_1_@_TrucKSide:	1
Inspection_Team_2_@_TrainSide:	1
Inspection_Team_2_@_TruckSide:	1
Inspection_Team_3_@_TruckSide:	1
Inspection_Team_4_@_TruckSide:	1
Light_1_Duty_Crane_@_TrainSide:	2
Light_2_Duty_Crane_@_TrainSide:	1
Light_Duty_Crane_1_@_TruckSide:	1
Light_Duty_Crane_2_@_TruckSide:	1
Light_Duty_Crane_3_@_TruckSide:	1
Values of Output Variables	
System total cost	ETB 1,426,646.55(Best one)

4.7. Comparison of current practices against optimal solution

The following Table compares the new value against the current practices in MDP CTO.

The results mainly focused on the assignment of resources at each station for both entities.

Table 4.13 shows the full details as follows:

Table 4.13: Comparison of current vs new optimal solution

No	Decision Variables	Current Practices	Optimal solution
1	Heavy_1_Duty_Crane_@_TrainSide:	2	1
2	Heavy_2_Duty_Crane_@_TrainSide:	2	1
3	Heavy_Duty_Crane_1_@_TruckSide:	2	1
4	Heavy_Duty_Crane_2_@_TruckSide:	2	1
5	Heavy_Duty_Crane_3_@_TruckSide:	2	1
6	Inspection_Team_1_@_TrainSide:	1	1
7	Inspection_Team_1_@_TrucKSide:	1	1
8	Inspection_Team_2_@_TrainSide:	1	1
9	Inspection_Team_2_@_TruckSide:	1	1
10	Inspection_Team_3_@_TruckSide:	1	1
11	Inspection_Team_4_@_TruckSide:	1	1
12	Light_1_Duty_Crane_@_TrainSide:	1	2
13	Light_2_Duty_Crane_@_TrainSide:	2	1
14	Light_Duty_Crane_1_@_TruckSide:	2	1
15	Light_Duty_Crane_2_@_TruckSide:	2	1
16	Light_Duty_Crane_3_@_TruckSide:	2	1
System number out		172	171
Trains Out		2.78	2.71
Truck Out		169.57	168.60
System total cost		1,623,973	1,426,646.55

Table 4.14 and Figure 4.7 shows the new configuration of resources has brought about 12% reduction of the total cost of MDP CTO which is a high achievement.

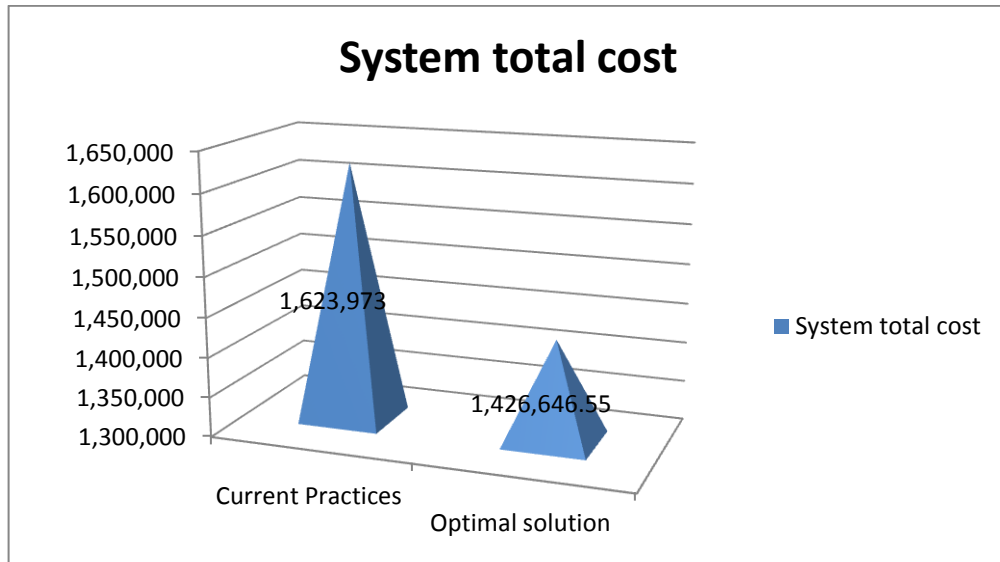


Figure 4.7: Comparison chart of current and optimal system total cost

The system numbers out for both cases are very closer to each and no significant change.

More summary of comparison is given in Table 4.14 as follows:

Table 4.14: Table Summary of comparison in current practice vs new optimization

Evaluation of	Current practice	Optimization suggestion	Difference	% of Change	Remark
System number out	172	171	1	0.58	Not significant
Trains Out	2.78	2.71	0.07	2.52	Not significant
Truck Out	169.57	168.6	0.97	0.57	Not significant
System total cost	1,623,973	1,426,646.55	197326.45	12.15	Very significant, positive gains

CHAPTER FIVE

5. CONCLUSIONS, RECOMMENDATION AND FUTURE WORKS

5.1. Conclusions

The main role of container terminal is the transfer and storage of containers. The performance of CT is of crucial importance for truck/trains and cargo owners who request quick service. It is mandatory to ensure a sufficiently short lay time for container in the port and to achieve further reduction of the terminal operating costs. For this reason, the management of CT must develop mechanisms to increase productivity when necessary.

A container terminal operation in MDP is a system with several subsystems and a large number of decisions for each subsystem. Due to the interactions of these subsystems, there is a lot of stochastic influence and interdependencies within the decisions which make an optimized operation of a whole container terminal very hard and without technical and methodical support hard to handle. One optimal operated subsystem influences all other subsystems and therefore does not result in optimality for the whole system.

In this thesis, optimization via simulation methodology was applied to the container terminal in order to decrease the cost and checking at two gates of trucks and trains. The built model provides an interesting mechanism for the decision-making, and the compact representation of the system to implement the strategy easier.

Optimization techniques were mainly used to get the optimal solution. Optimization is also an effective tool for modeling system with strong uncertainties. In this thesis the researcher developed a simulation model that can be used to optimize the container terminal operations and analyze the key performance indicators using Arena software fully package.

The objective of the model was assessing the key performance indicators for the betterment of the container terminal as a whole. Under a case study of the MDP, the study attempted to answer the following questions:

- I. What are the waiting line performance parameters to be estimated via simulation?
- II. What is a working model for container terminal operation?
- III. What is the optimum cost to run the container terminal operation?

Findings revealed that container terminal operations under given resources, entities, queue and process in summarized way as follows:

- The optimal cost of system was found to be Birr 1,426,646.55 and each resource assigned per respective position in Table 13. This means that the model resulted in a better equipment and inspection team utilization than the methods that MDP planners use.
- The study found percentage of usage of new optimized simulation model about 60%, idle about 19% and busy about 20% in the MDP CTO.
- The system number out from the MDP found to be about 169 trucks and 2.7 trains which pushed about 600TEU per day operations, 18,000 TEU per month and 216,000 TEU per annual which is better throughput than MDP planners use of 136,038 TEU per annum.
- The study shifts the current working time from 12 hours a day to 18 hours a day for overall optimality.
- The study improves the MDP CTO by 12% of its total operation cost with the closer output of entities.

The study would serve as an initiation for those who interested to conduct a detailed and comprehensive study regarding the other dry port terminal operation in Ethiopia. The

significances are assessing waiting performances, modeling MDP CTO, lesser cost and cheap time, and risk free research style.

If it cannot optimize the total cost of the system MDP CTO in higher depth and details, the competitiveness and logistics hub of MDP will incur a lot of cost and time. More research and innovation are needed to keep CTO running at optimal cost while still providing required services for all entities at required standards.

5.2.Recommendations

The recommendations were made based on the observed gaps and in a way that answers the major research questions and with intention to meet the objectives of the study. The study was conducted to find out the optimal container terminal operations in a case of MDP using simulation. The recommendation highlighted as follows:

- The company should have to see new configuration of resources to keep the balance of the system number out and system total cost.
- The company should work for 18 hours a day, 7 days a week and 365 days a year for overall optimality.
- The company should understand a unit percentage of total cost reduction has a high impact on the optimal run of the system.
- The company should have to find any better decision supporting mechanism for the system and taking always more & always better.
- The company should look for research works to keep CTO running at optimal cost while still providing required services for all entities at required standards.

5.3.Future works

Under the simulation analytics framework, simulation is used to generate “what-if” scenarios that might happen in the future, while the optimization is employed to find the best decisions for that particular scenario. Therefore, learning models of either statistical meta-modeling or machine learning methods should be developed to identify the relationship between scenarios and the respective best decision to minimize time spent on optimization via simulation under presented thesis to more depth and detail.

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APPENDIX

I. Trucks inter arrival time

Figure 7.1 obtained as result of the input data distribution from Table 4.2. The histogram has 10 intervals and its range from 0 to 19. It was found that the distribution to be exponential with EXP (4) and square error of 0.010259. The Chi square test gave number of interval 6, degree of freedom 4, test statistic of 6.83 and corresponding value p-value of 0.16.

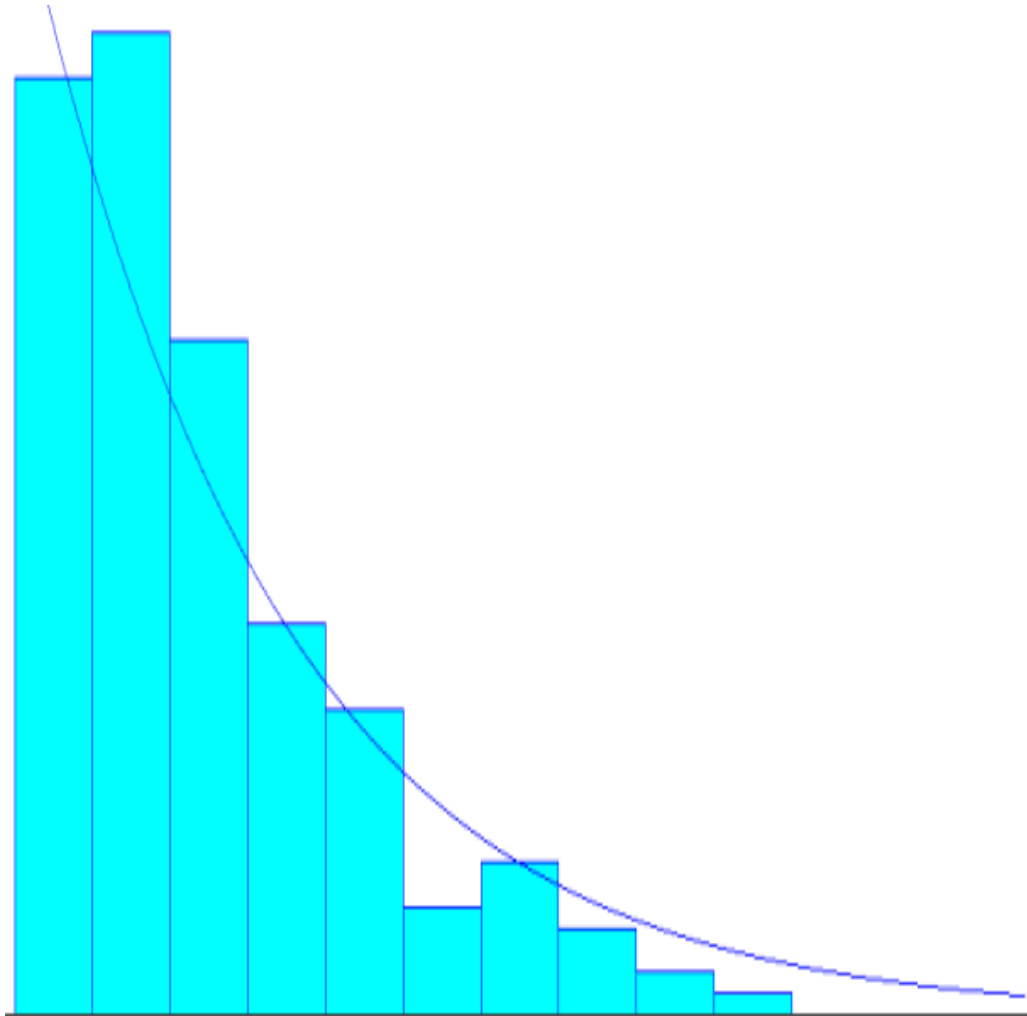


Figure 7.1: Trucks inter arrival between any successive

II. Trains inter arrival time

Figure 7.2 as result of the input data distribution from Table 4.1. The histogram has 8 intervals and its range from 31 to 551. It was found that the distribution to be exponential with EXP (120) and square error of 0.007376. The Chi square test gave number of interval 4, degree of freedom 2, test statistic of 1.7 and corresponding value p-value of 0.443.

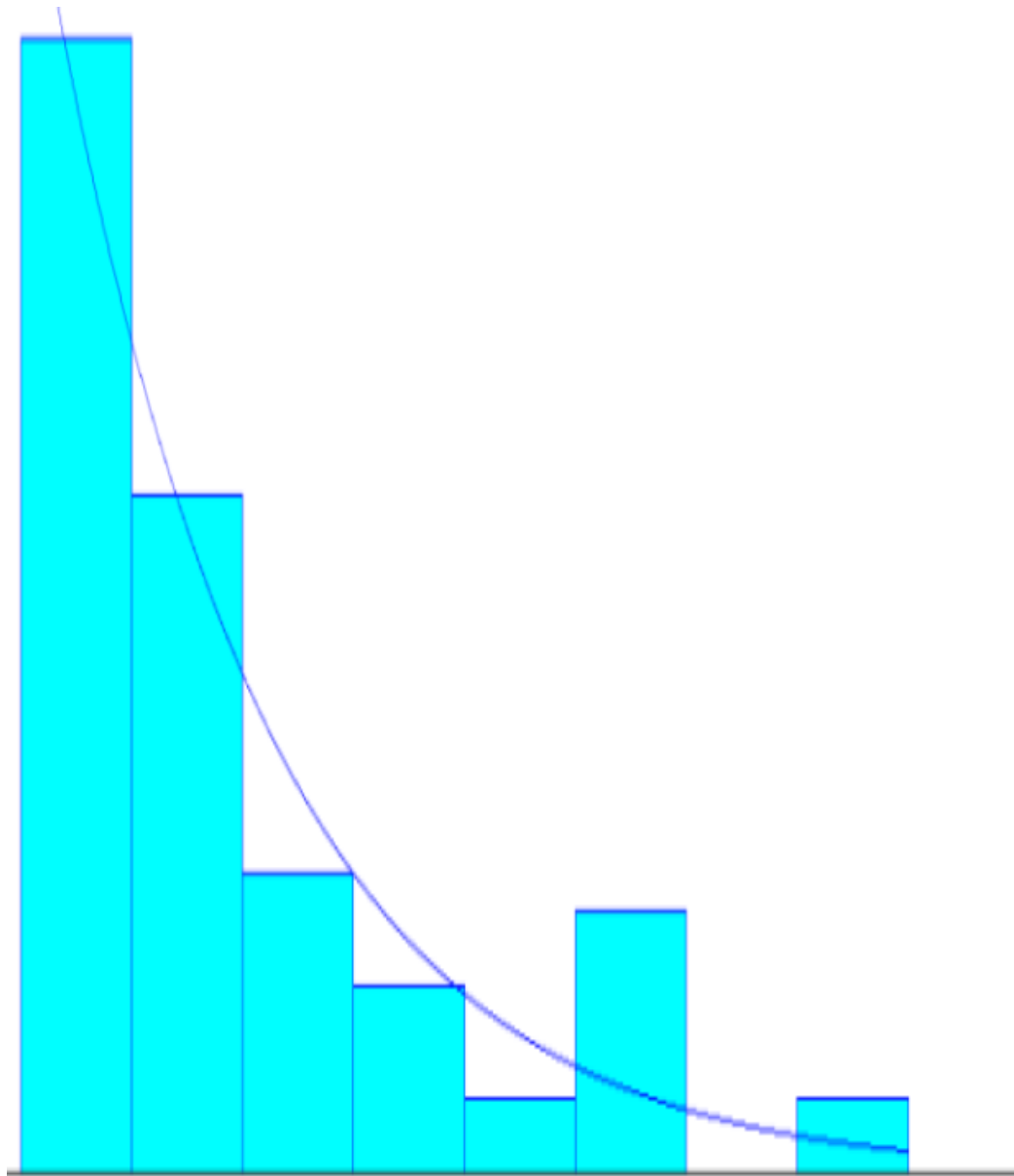


Figure 7.2: Train inter arrival between any successive

III. Trucks' gate check- up for in/out

Table 7.1 shows the trucks' gate check-up for in/out operations and the time take to release. The number of trucks was 170 .The values of the data are maximum value of 8 minutes, minimum value of 3, sample mean of 5 and sample of standard deviation of 1.09.

Table 7.1: Trucks' gate check-up for in/out

Trucks	Minute _s	Trucks	Minute _s	Trucks	Minute _s	Trucks	Minute _s	Trucks	Minute _s	Trucks	Minute _s
1	5	31	5	61	5	91	4	121	5	151	6
2	6	32	6	62	4	92	4	122	5	152	6
3	4	33	4	63	4	93	5	123	5	153	3
4	4	34	6	64	5	94	5	124	5	154	5
5	4	35	5	65	5	95	7	125	5	155	8
6	5	36	6	66	6	96	5	126	4	156	5
7	6	37	7	67	6	97	5	127	5	157	5
8	4	38	5	68	4	98	7	128	7	158	5
9	6	39	5	69	5	99	6	129	5	159	5
10	6	40	6	70	3	100	6	130	6	160	7
11	6	41	6	71	7	101	4	131	4	161	5
12	6	42	6	72	5	102	6	132	4	162	5
13	5	43	4	73	4	103	5	133	6	163	6
14	6	44	4	74	5	104	6	134	6	164	7
15	5	45	4	75	4	105	4	135	5	165	5
16	6	46	5	76	6	106	5	136	4	166	5
17	6	47	6	77	5	107	6	137	5	167	5
18	5	48	5	78	5	108	8	138	6	168	5
19	4	49	4	79	4	109	8	139	5	169	4
20	6	50	4	80	8	110	5	140	6	170	7
21	7	51	6	81	4	111	6	141	5		
22	5	52	6	82	6	112	5	142	7		
23	5	53	5	83	6	113	6	143	4		
24	5	54	5	84	4	114	6	144	5		
25	4	55	5	85	3	115	6	145	8		
26	5	56	6	86	6	116	6	146	6		
27	4	57	4	87	6	117	7	147	7		
28	5	58	4	88	7	118	4	148	5		
29	3	59	6	89	4	119	4	149	6		
30	7	60	5	90	4	120	8	150	7		

Figure 7.3 obtained as result of the input data distribution from Table 7.1. The histogram has 6 intervals and its range from 3 to 8. It was found that the distribution to be triangular with TRIA (3, 5, 8) and square error of 0.009588. The Chi square test gave number of interval 5, degree of freedom 3, test statistic of 15.3 and corresponding value p-value of 0.16.

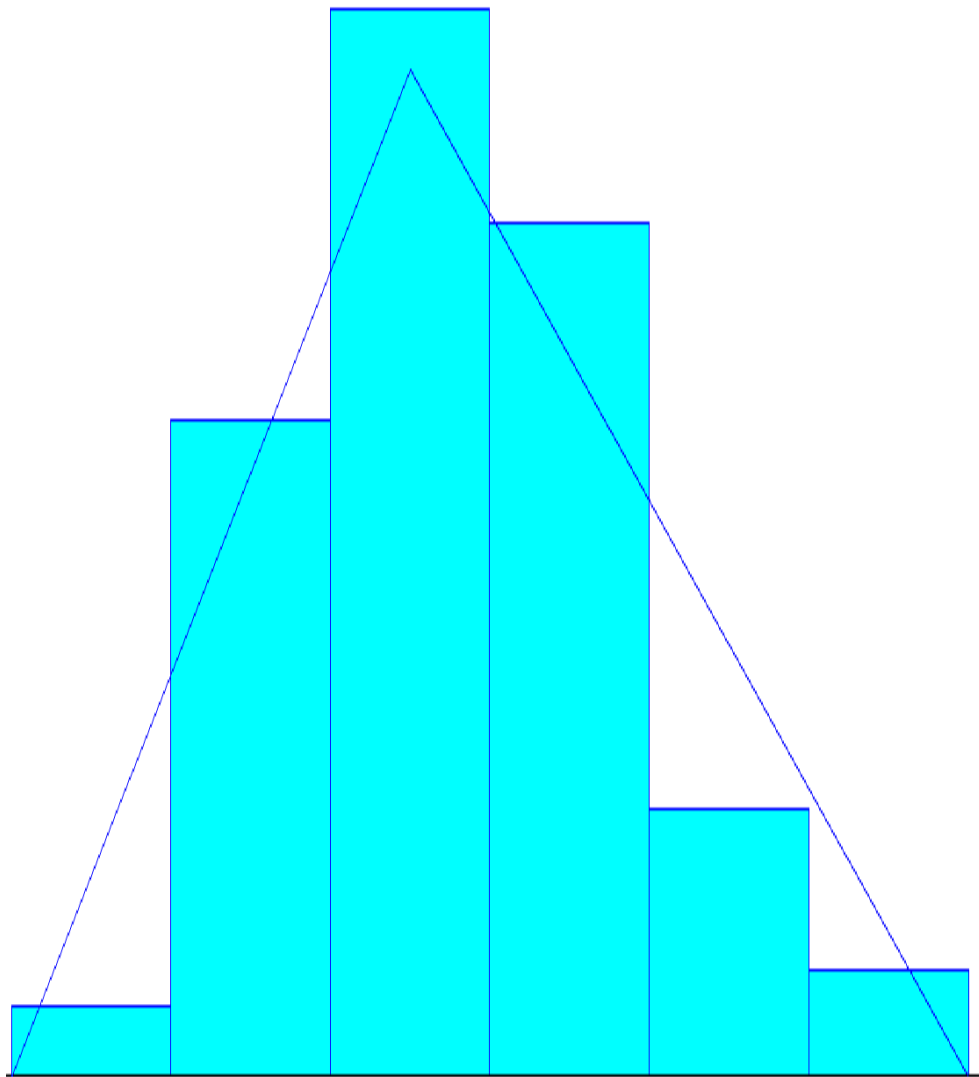


Figure 7.3: Trucks' gate check-up for in/out

IV. Train side check-up for in/out

Table 7.2 shows the train side check-up for in/out operations and the time take to release. The number of trains was 72 .The values of the data are maximum value of 60 minutes, minimum value of 30, sample mean of 45 and sample of standard deviation of 5.92.

Table 7.2: Train side check-up for in/out

Trains	Minutes	Trains	Minutes	Trains	Minutes	Trains	Minutes	Trains	Minutes	Trains	Minutes
1	41	15	50	29	37	43	45	57	40	71	53
2	46	16	47	30	48	44	50	58	30	72	55
3	50	17	46	31	51	45	55	59	41		
4	45	18	40	32	51	46	50	60	40		
5	37	19	48	33	56	47	39	61	47		
6	47	20	49	34	42	48	48	62	40		
7	48	21	57	35	45	49	46	63	47		
8	44	22	47	36	41	50	35	64	45		
9	58	23	50	37	45	51	45	65	52		
10	35	24	44	38	50	52	42	66	43		
11	41	25	47	39	60	53	42	67	44		
12	43	26	52	40	46	54	55	68	42		
13	49	27	36	41	39	55	56	69	35		
14	51	28	43	42	47	56	37	70	44		

Figure 7.4 obtained as result of the input data distribution from Table 7.2. The histogram has 8 intervals and its range from 30 to 60. It was found that the distribution to be triangular with TRIA (30, 45, 60) and square error of 0.010621. The Chi square test gave number of interval 6, degree of freedom 4, test statistic of 0.632 and corresponding value p-value of 0.75.

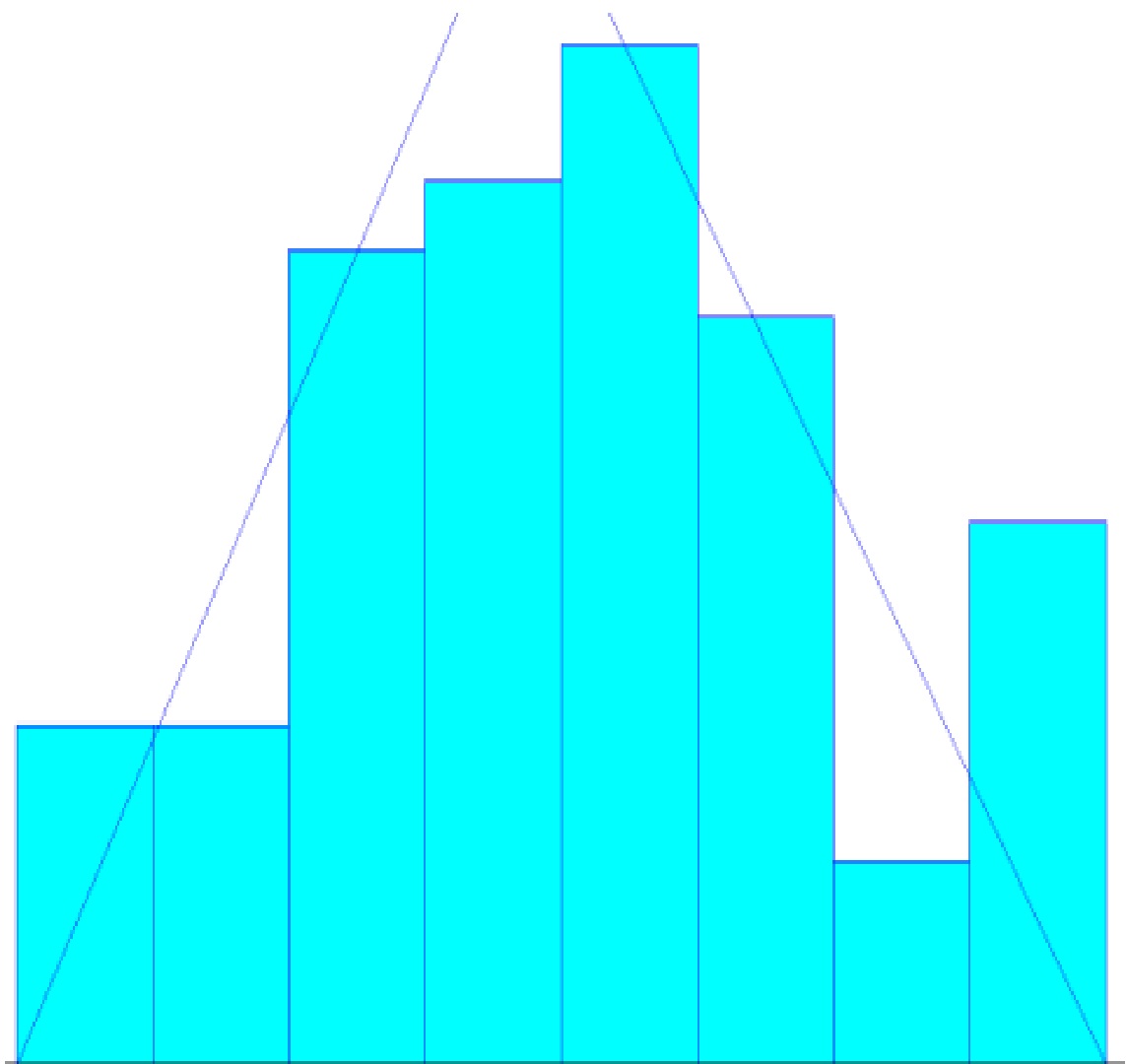


Figure 7.4: Train side Check-up for in/out

V. Queue in yard operations or delay of trucks

Table 7.3 shows the trucks queue at yard operations and the time take to release. The number of trucks was 170 .The values of the data are maximum value of 27 minutes, minimum value of 0, sample mean of 4.22 and sample of standard deviation of 4.5.

Table 7.3: Trucks queue @ yard operations

Trucks	Minute _s	Trucks	Minute _s	Trucks	Minute _s	Trucks	Minute _s	Trucks	Minute _s	Trucks	Minute _s
1	3	31	0	61	4	91	1	121	16	151	2
2	0	32	3	62	6	92	7	122	3	152	3
3	26	33	2	63	2	93	1	123	2	153	9
4	3	34	3	64	6	94	1	124	0	154	3
5	1	35	1	65	2	95	2	125	2	155	3
6	4	36	14	66	12	96	21	126	1	156	3
7	2	37	2	67	6	97	4	127	0	157	1
8	2	38	5	68	1	98	0	128	2	158	1
9	8	39	4	69	5	99	2	129	12	159	11
10	3	40	8	70	1	100	3	130	9	160	3
11	7	41	3	71	10	101	2	131	3	161	8
12	8	42	3	72	2	102	2	132	4	162	4
13	10	43	0	73	1	103	1	133	2	163	2
14	1	44	12	74	2	104	7	134	3	164	8
15	0	45	5	75	17	105	2	135	6	165	0
16	2	46	2	76	6	106	11	136	4	166	7
17	6	47	4	77	0	107	3	137	2	167	2
18	3	48	1	78	5	108	5	138	2	168	1
19	3	49	1	79	3	109	7	139	1	169	3
20	2	50	11	80	9	110	6	140	0	170	7
21	6	51	3	81	0	111	1	141	2		
22	6	52	1	82	3	112	1	142	13		
23	4	53	4	83	0	113	2	143	0		
24	3	54	1	84	2	114	1	144	1		
25	0	55	0	85	27	115	10	145	3		
26	3	56	9	86	2	116	1	146	1		
27	1	57	4	87	0	117	4	147	6		
28	19	58	4	88	3	118	3	148	4		
29	8	59	1	89	2	119	2	149	2		
30	4	60	4	90	4	120	5	150	7		

Figure 7.5 obtained as result of the input data distribution from Table 7.3. The histogram has 13 intervals and its range from 0 to 27. It was found that the distribution to be exponential with EXP (4) and square error of 0.025085. The Chi square test gave number of interval 6, degree of freedom 4, test statistic of 17.3 and corresponding value p-value of 0.16.

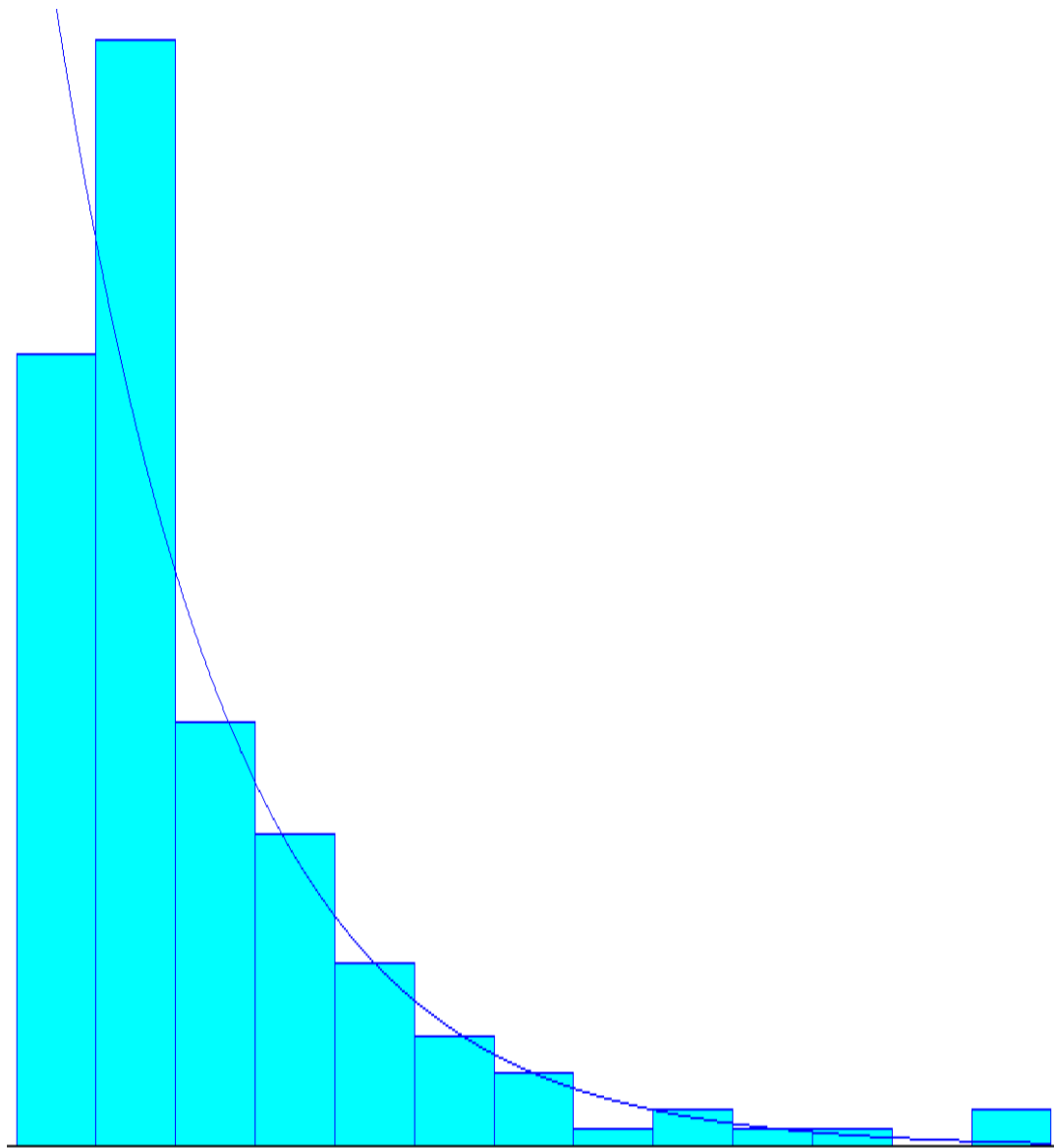


Figure 7.5: Trucks queue @ yard operations

VI. Queue of trains in MDP

Table 7.4 shows the trains queue at train side operations and the time take to release. The number of trains was 72. The values of the data are maximum value of 369 minutes, minimum value of 60, sample mean of 154 and sample of standard deviation of 82.9.

Table 7.4: Trains queue at train side operations

Trains	Minutes	Trains	Minutes	Trains	Minutes	Trains	Minutes	Trains	Minutes	Trains	Minutes
1	76	15	118	29	210	43	80	57	181	71	334
2	129	16	119	30	154	44	133	58	214	72	345
3	358	17	66	31	285	45	114	59	271		
4	319	18	147	32	201	46	94	60	113		
5	116	19	93	33	84	47	82	61	200		
6	185	20	236	34	276	48	138	62	98		
7	150	21	73	35	344	49	64	63	166		
8	79	22	60	36	66	50	74	64	90		
9	66	23	118	37	224	51	138	65	151		
10	147	24	119	38	122	52	175	66	140		
11	93	25	72	39	137	53	142	67	69		
12	236	26	72	40	71	54	62	68	108		
13	73	27	62	41	103	55	262	69	111		
14	60	28	259	42	154	56	111	70	131		

Figure 7.6 obtained as result of the input data distribution from Table 7.4. The histogram has 8 intervals and its range from 60 to 369. It was found that the distribution to be exponential with EXP (100) and square error of 0.007831. The Chi square test gave number of interval 4, degree of freedom 2, test statistic of 1.78 and corresponding value p-value of 0.43.

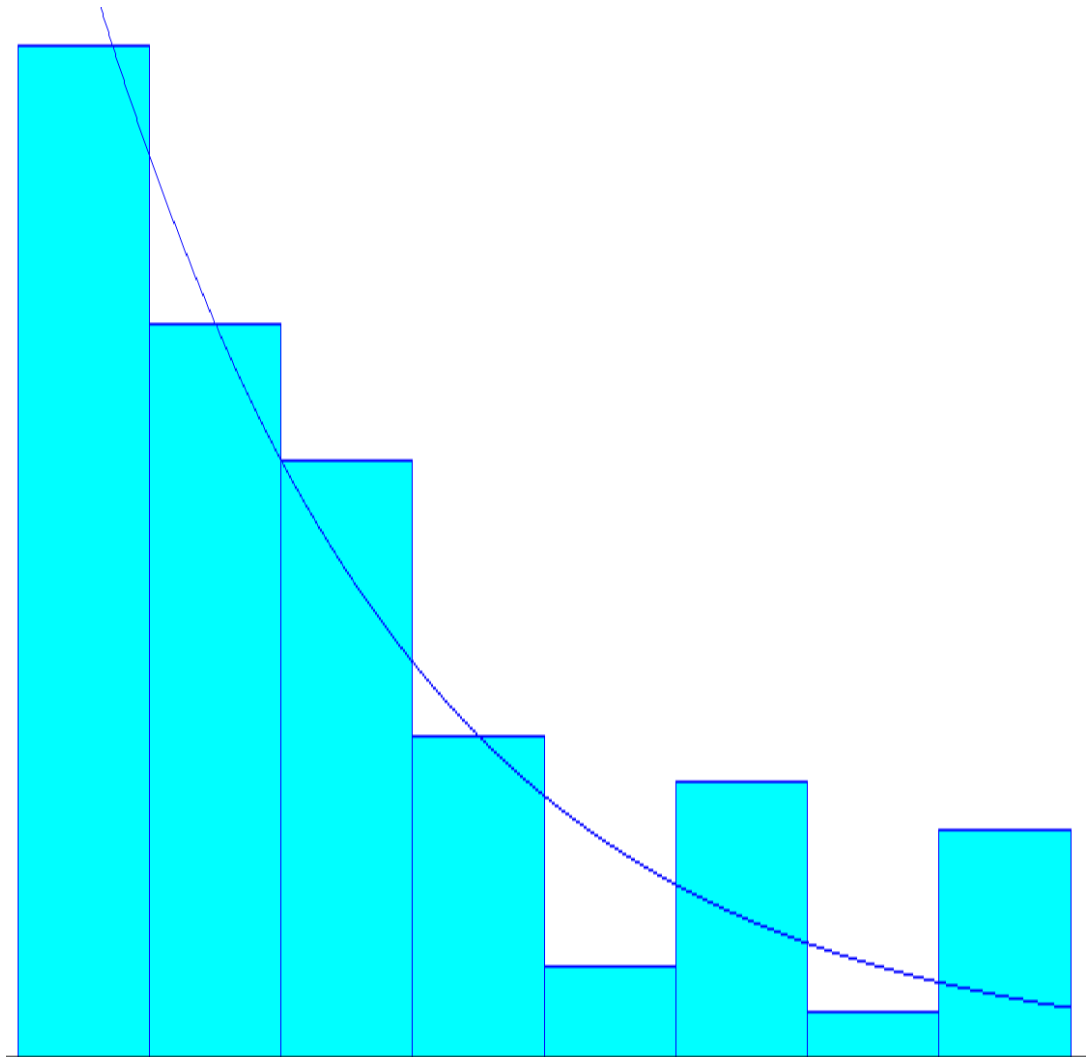


Figure 7.6: Trains queue at train side operations

VII. Loading/unloading a truck with FC

Table 7.5 shows loading/unloading a truck with FC using heavy duty crane and the time take to release. The number of trucks was 90 .The values of the data are maximum value of 15minutes, minimum value of 5,sample mean of 10 and sample of standard deviation of 2.04.

Table 7.5: Loading/unloading a truck with FC

Trucks	Minutes	Trucks	Minutes	Trucks	Minutes	Trucks	Minutes	Trucks	Minutes	Trucks	Minutes
1	8	16	7	31	10	46	14	61	9	76	9
2	9	17	11	32	12	47	8	62	12	77	12
3	9	18	13	33	12	48	6	63	8	78	9
4	11	19	11	34	10	49	7	64	8	79	9
5	10	20	8	35	10	50	12	65	11	80	11
6	13	21	13	36	11	51	10	66	14	81	11
7	15	22	8	37	9	52	9	67	8	82	12
8	10	23	10	38	8	53	8	68	13	83	9
9	12	24	12	39	9	54	10	69	14	84	8
10	7	25	12	40	9	55	12	70	11	85	9
11	12	26	14	41	8	56	10	71	7	86	9
12	10	27	12	42	10	57	13	72	8	87	10
13	8	28	11	43	14	58	11	73	10	88	11
14	9	29	9	44	10	59	13	74	10	89	5
15	12	30	13	45	10	60	12	75	10	90	8

Figure 7.7 obtained as result of the input data distribution from Table 7.5. The histogram has 10 intervals and its range from 5 to 15. It was found that the distribution to be triangular with TRIA (5, 10, 15) and square error of 0.004548. The Chi square test gave number of interval 6, degree of freedom 4, test statistic of 1.66 and corresponding value p-value of 0.75.

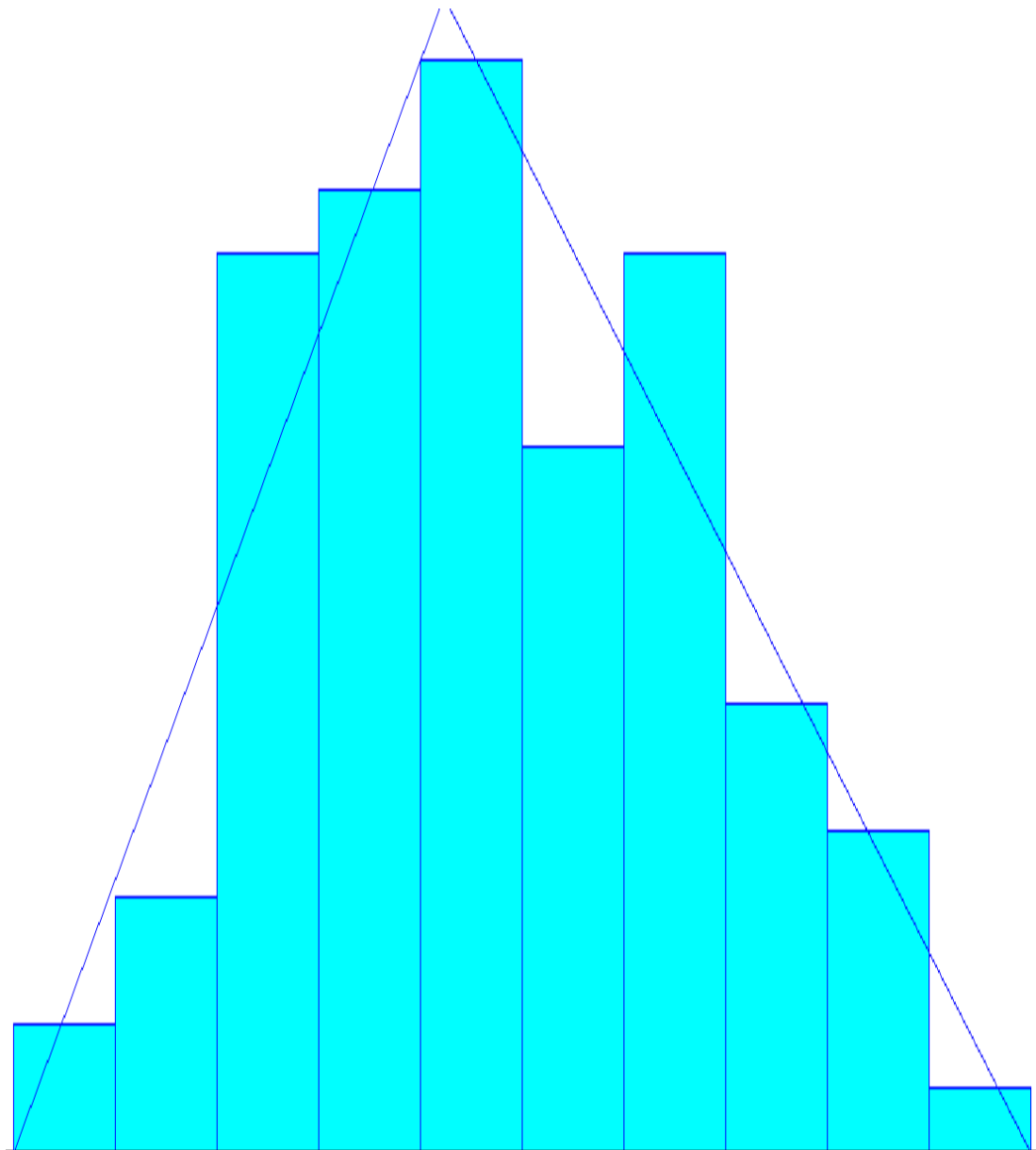


Figure 7.7: Loading/unloading a truck with FC

VIII. Loading/unloading at train with FC

Table 7.6 shows loading/unloading a train with FC using heavy duty crane and the time take to release. The number of trains was 38 .The values of the data are maximum value of 114 minutes, minimum value of 64, sample mean of 94.6 and sample of standard deviation of 10.7.

Table 7.6: Loading/unloading a train with FC

Trains	Minutes	Trains	Minutes	Trains	Minutes	Trains	Minutes
1	77	11	80	21	69	31	81
2	86	12	82	22	76	32	88
3	88	13	97	23	76	33	94
4	89	14	89	24	75	34	78
5	95	15	90	25	71	35	76
6	84	16	114	26	95	36	89
7	64	17	94	27	76	37	102
8	107	18	76	28	97	38	76
9	83	19	105	29	88		
10	74	20	85	30	71		

Figure 7.8 obtained as result of the input data distribution from Table7.6.The histogram has 6 intervals and its range from 64 to 114. It was found that the distribution to be triangular with TRIA (68.5, 78.5, 109) and square error of 0.008044. The Chi square test gave number of interval 3, degree of freedom 1, test statistic of 0.532 and corresponding value p-value of 0.478.

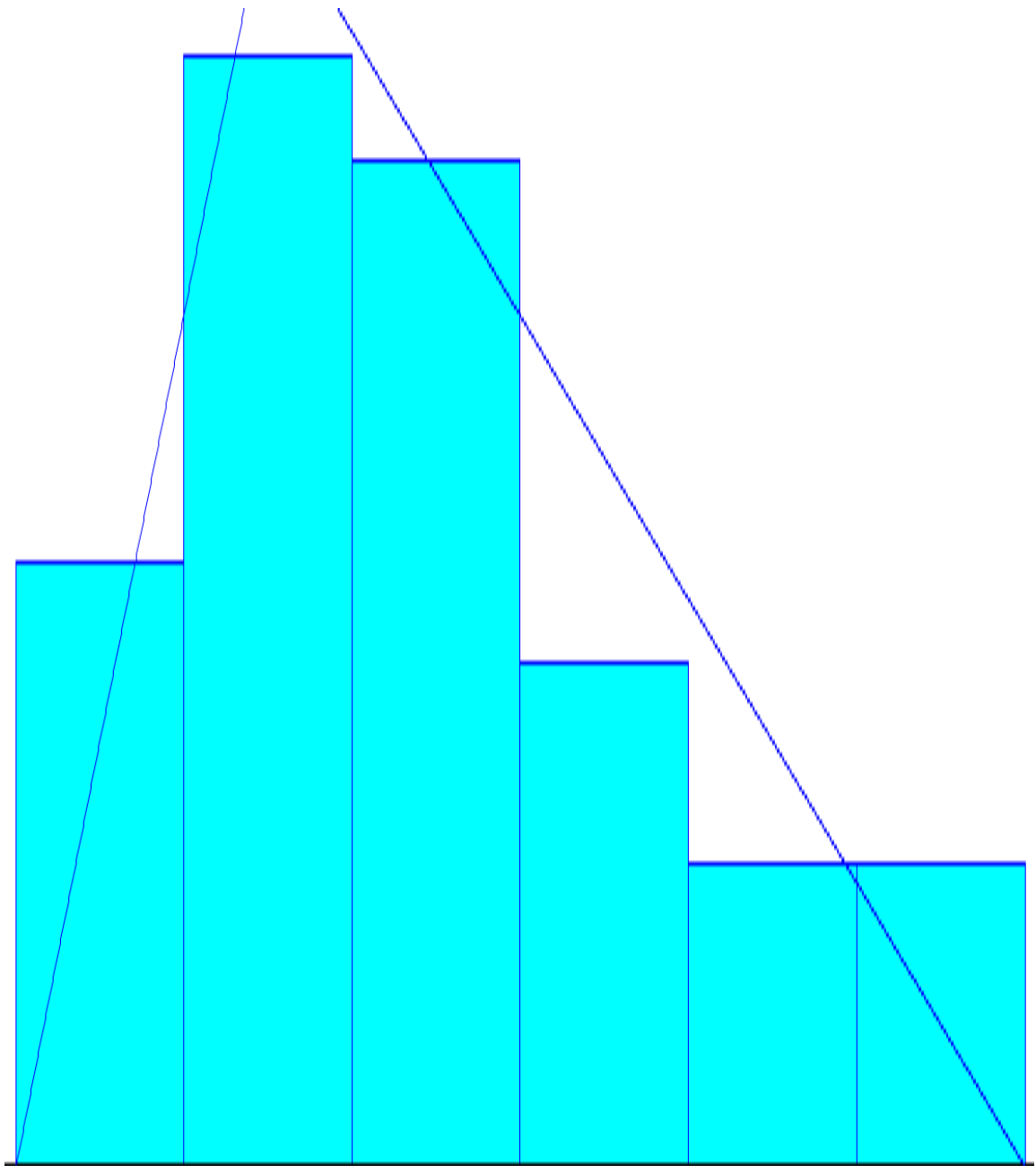


Figure 7.8: Loading/unloading a train with FC

IX. Loading/unloading a truck with EC

Table 7.7 shows loading/unloading a truck with EC using light duty crane and the time take to release. The number of trucks was 80 .The values of the data are maximum value of 15 minutes, minimum value of 5, sample mean of 10 and sample of standard deviation of 1.98

Table 7.7: Loading/unloading a truck with EC

Trucks	Minutes	Trucks	Minutes	Trucks	Minutes	Trucks	Minutes	Trucks	Minutes	Trucks	Minutes
1	11	16	5	31	9	46	6	61	9	76	12
2	7	17	11	32	14	47	11	62	11	77	12
3	9	18	12	33	7	48	8	63	8	78	12
4	9	19	11	34	9	49	10	64	9	79	10
5	12	20	10	35	11	50	7	65	10	80	13
6	10	21	10	36	9	51	14	66	10		
7	10	22	11	37	11	52	14	67	10		
8	11	23	11	38	6	53	13	68	10		
9	11	24	12	39	9	54	9	69	9		
10	9	25	11	40	10	55	11	70	12		
11	12	26	11	41	8	56	15	71	11		
12	11	27	11	42	9	57	7	72	11		
13	10	28	14	43	9	58	8	73	11		
14	9	29	9	44	7	59	8	74	13		
15	6	30	9	45	12	60	12	75	11		

Figure 7.9 obtained as result of the input data distribution from Table 7.7. The histogram has 9 intervals and its range from 5 to 15. It was found that the distribution to be triangular with TRIA (5, 10, 15) and square error of 0.008044. The Chi square test gave number of interval 6, degree of freedom 4, test statistic of 0.385 and corresponding value p-value of 0.44.

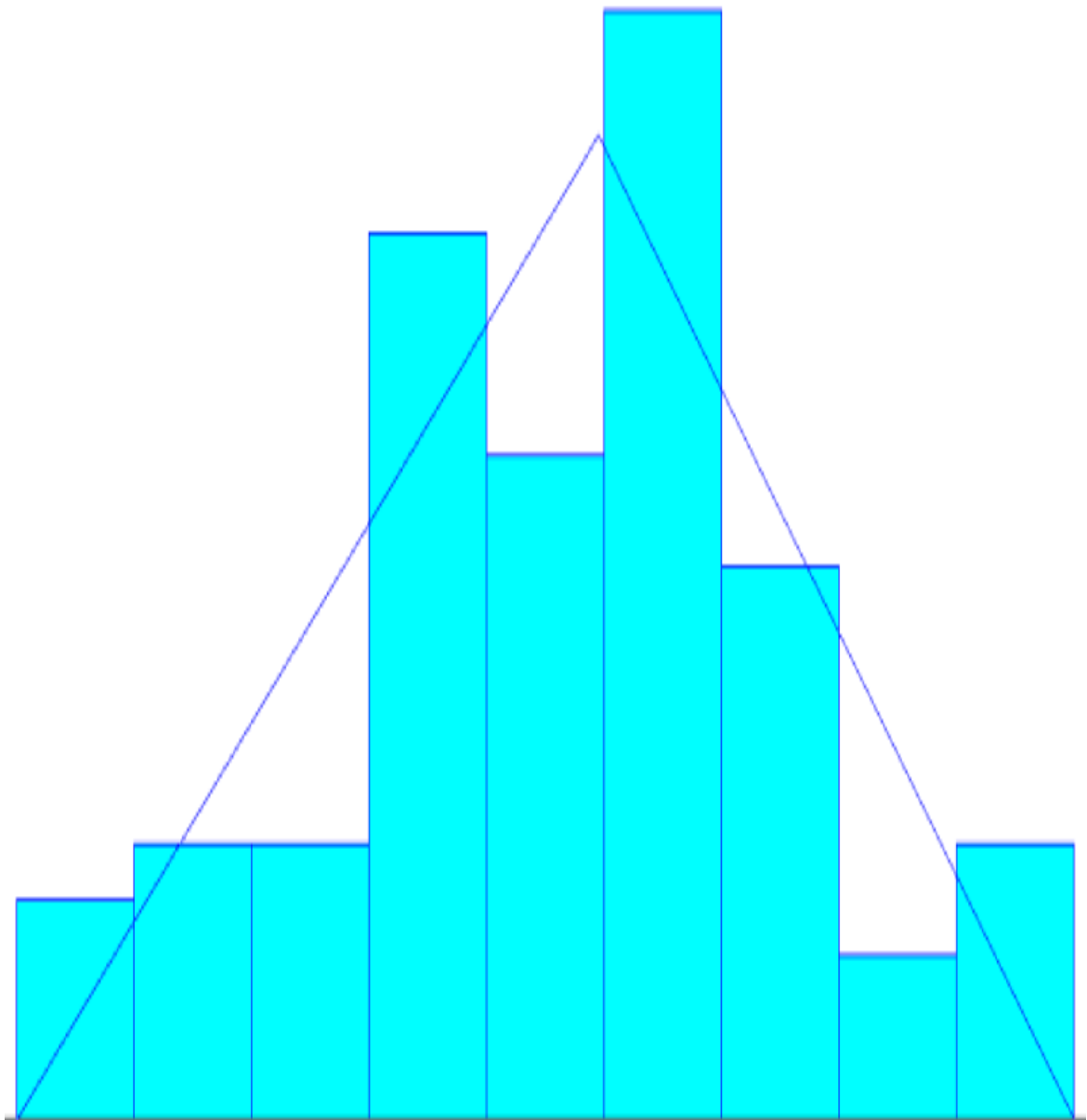


Figure 7.9: Loading/unloading a truck with EC

X. Loading/unloading train with EC

Table 7.8 shows loading/unloading a train with EC using light duty crane and the time take to release. The number of trucks was 34 .The values of the data are maximum value of 123 minutes, minimum value of 73, sample mean of 92.4 and sample of standard deviation of 10.6

Table 7.8: Loading/unloading a train with EC

Trains	Minutes	Trains	Minutes	Trains	Minutes	Trains	Minutes
1	112	11	108	21	91	31	123
2	104	12	92	22	92	32	92
3	113	13	91	23	102	33	99
4	95	14	76	24	79	34	111
5	103	15	94	25	105		
6	95	16	90	26	93		
7	85	17	97	27	88		
8	83	18	88	28	94		
9	97	19	92	29	111		
10	84	20	73	30	107		

Figure 7.10 obtained as result of the input data distribution from Table 7.8. The histogram has 6 intervals and its range from 73 to 123. It was found that the distribution to be triangular with TRIA (73, 92.4, 123) and square error of 0.008044. The Chi square test gave number of interval 6, degree of freedom 4, test statistic of 0.385 and corresponding value p-value of 0.15.

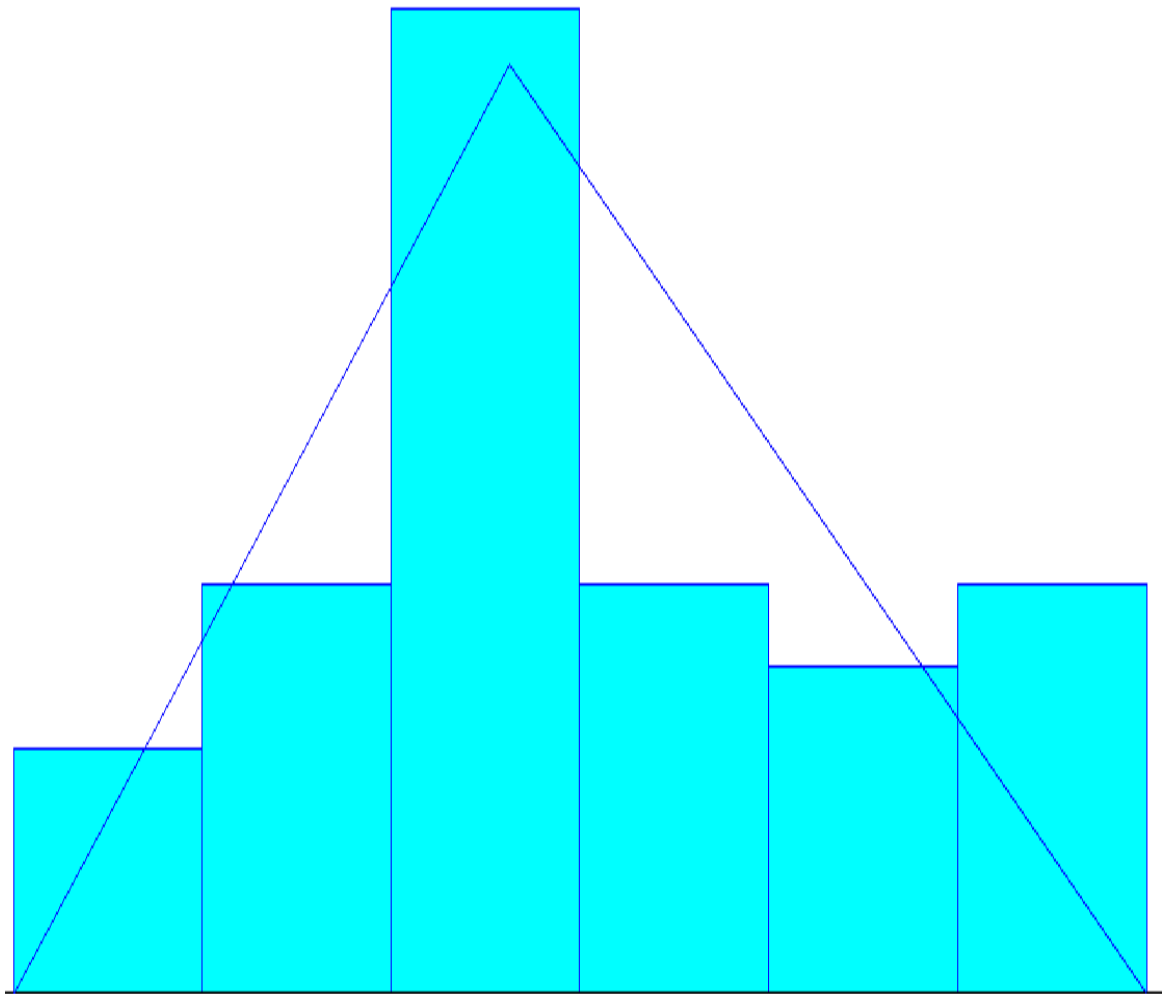
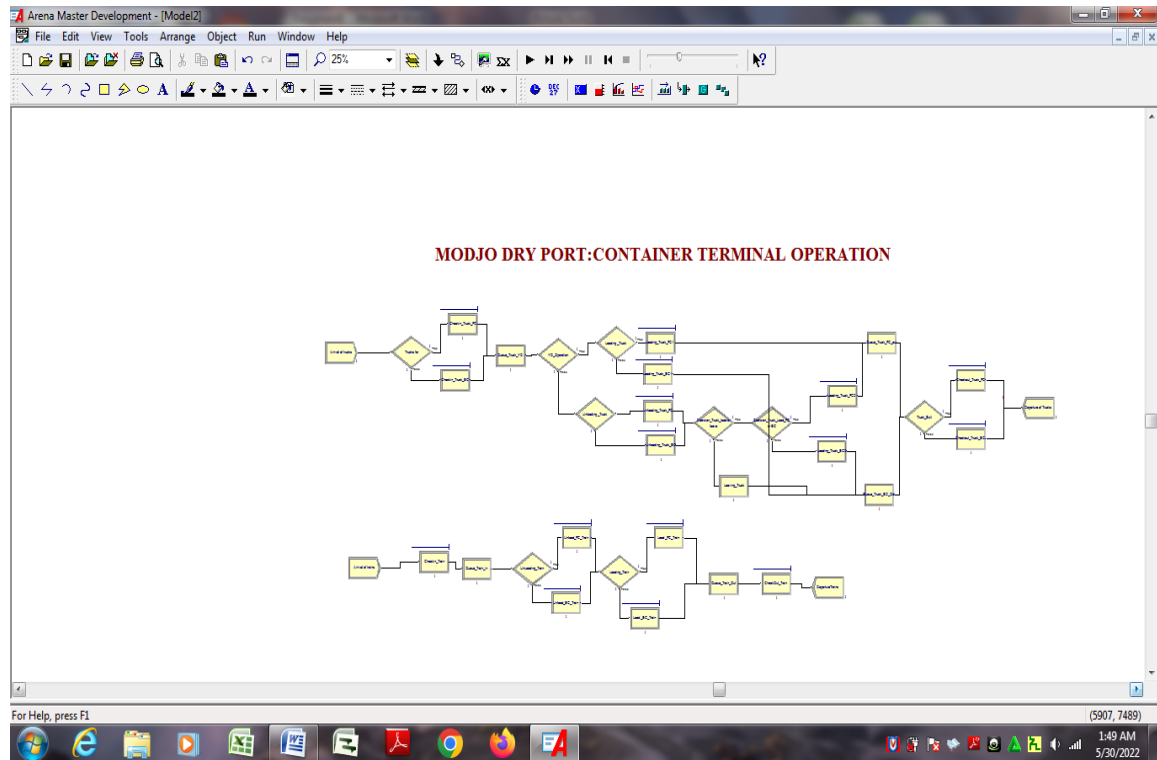


Figure 7.10: Loading/unloading a train with EC

XI. Samples of simulation model

The following Figures are the print screen from the computer laptop while working the simulation model.



		Resource - Basic Process								
	Name	Type	Capacity	Busy / Hour	Idle / Hour	Per Use	StateSet Name	Failures	Report Statistics	
1	Inspection_Team_2_@_TruckSide	Fixed Capacity	1	1000	500	750		0 rows	✓	
2	Heavy_Duty_Crane_3_@_TruckSide	Fixed Capacity	1	2000	1000	1500		0 rows	✓	
3	Inspection_Team_4_@_TruckSide	Fixed Capacity	1	1000	500	750		0 rows	✓	
4	Heavy_Duty_Crane_2_@_TruckSide	Fixed Capacity	1	2000	1000	1500		0 rows	✓	
5	Light_Duty_Crane_2_@_TruckSide	Fixed Capacity	1	1000	500	750		0 rows	✓	
6	Light_Duty_Crane_3_@_TruckSide	Fixed Capacity	1	1000	500	750		0 rows	✓	
7	Heavy_Duty_Crane_1_@_TruckSide	Fixed Capacity	1	2000	1000	1500		0 rows	✓	
8	Light_Duty_Crane_1_@_TruckSide	Fixed Capacity	1	1000	500	750		0 rows	✓	
9	Heavy_1_Duty_Crane_@_TrainSide	Fixed Capacity	1	10000	5000	7500		0 rows	✓	
10	Heavy_2_Duty_Crane_@_TrainSide	Fixed Capacity	1	10000	5000	7500		0 rows	✓	
11	Light_2_Duty_Crane_@_TrainSide	Fixed Capacity	1	5000	2500	3750		0 rows	✓	
12	Light_1_Duty_Crane_@_TrainSide	Fixed Capacity	1	5000	2500	3750		0 rows	✓	
13	Inspection_Team_1_@_TrainSide	Fixed Capacity	1	5000	2500	3750		0 rows	✓	
14	Inspection_Team_2_@_TrainSide	Fixed Capacity	1	5000	2500	3750		0 rows	✓	
15	Inspection_Team_1_@_TruckSide	Fixed Capacity	1	1000	500	750		0 rows	✓	
16	Inspection_Team_3_@_TruckSide	Fixed Capacity	1	1000	500	750		0 rows	✓	

Double click here to add a new row

Batch		Separate		Queue - Basic Process								
				Name	Type	Shared	Report Statistics					
				1	Checkin_Truck_FC.Queue	First In First Out	<input type="checkbox"/>	<input checked="" type="checkbox"/>				
				2	Checkin_Truck_EC.Queue	First In First Out	<input type="checkbox"/>	<input checked="" type="checkbox"/>				
				3	Loading_Truck_FC2.Queue	First In First Out	<input type="checkbox"/>	<input checked="" type="checkbox"/>				
				4	Checkout_Truck_FC.Queue	First In First Out	<input type="checkbox"/>	<input checked="" type="checkbox"/>				
				5	Checkout_Truck_EC.Queue	First In First Out	<input type="checkbox"/>	<input checked="" type="checkbox"/>				
				6	Unloading_Truck_FC.Queue	First In First Out	<input type="checkbox"/>	<input checked="" type="checkbox"/>				
				7	Unloading_Truck_EC.Queue	First In First Out	<input type="checkbox"/>	<input checked="" type="checkbox"/>				
				8	Loading_Truck_EC2.Queue	First In First Out	<input type="checkbox"/>	<input checked="" type="checkbox"/>				
				9	Loading_Truck_FC1.Queue	First In First Out	<input type="checkbox"/>	<input checked="" type="checkbox"/>				
				10	Loading_Truck_EC1.Queue	First In First Out	<input type="checkbox"/>	<input checked="" type="checkbox"/>				
				11	Unload_FC_Train.Queue	First In First Out	<input type="checkbox"/>	<input checked="" type="checkbox"/>				
				12	Load_FC_Train.Queue	First In First Out	<input type="checkbox"/>	<input checked="" type="checkbox"/>				
				13	Load_EC_Train.Queue	First In First Out	<input type="checkbox"/>	<input checked="" type="checkbox"/>				
				14	Unload_EC_Train.Queue	First In First Out	<input type="checkbox"/>	<input checked="" type="checkbox"/>				
				15	Checkin_Train.Queue	First In First Out	<input type="checkbox"/>	<input checked="" type="checkbox"/>				
				16	CheckOut_Train.Queue	First In First Out	<input type="checkbox"/>	<input checked="" type="checkbox"/>				

Batch		Separate		Entity - Basic Process								
				Entity Type	Initial Picture	Holding Cost / Hour	Initial VA Cost	Initial NVA Cost	Initial Waiting Cost	Initial Tran Cost	Initial Other Cost	Report Statistics
				1	Trucks	Picture.Report	200	0.0	0.0	0.0	0.0	<input checked="" type="checkbox"/>
				2	Trains	Picture.Report	10000	0.0	0.0	0.0	0.0	<input checked="" type="checkbox"/>

Figure 7.11: Samples of simulation model print screen