Modeling Raw Material Inventory Control and Delivery of Ready Mixed Concrete to Sites in Addis Ababa

By

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APPROVAL PAGE

"Modeling Raw Material Inventory Control and Delivery of Ready Mixed Concrete to Sites in Addis Ababa"

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DECLARATION

I declare that this research work entitled "**Modeling Raw Material Inventory Control and Delivery of Ready Mixed Concrete to Sites in Addis Ababa**" is my original work, with the guidance of my advisor, this research has not been presented to any other university.

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ABSTRACT

Due to the city's booming construction, ready-mixed concrete is gaining wide recognition and has a high demand in Addis Ababa. Since these operations are performed in a highly uncertain environment, making planning and operating difficult and complex. So a supply chain management system is needed to form a consumption pattern for the raw materials of RMC and delivery of RMC. Inventory and delivery are the most important among the several management plans and decisions in RMC batching plants, such a raw material inventory control system of RMC batching plants could be applied as an approach for optimal estimation of the reservoirs required for storage of raw materials and to reduce the effect of uncertainties on delivery operations. This research aims to develop an integrated raw materials inventory model with a simulation model for the delivery of RMC to sites in Addis Ababa. The data sources used in this research are observation and financial reports using a case study plant and delivery sites. A raw material inventory model was developed through Economic Order Quantity (EOQ) model and the developed models are predicted using Artificial Neural Network (ANN). As a result, the testing predictive analysis results confirmed that the ANN predictive had higher accuracy in the prediction of the optimal order quantity and reordering point (ROP) of raw materials with an accuracy measurement value of 0.98 R and 0.2935 MAE and 0.9998 R and 0.2935 MAE for EOQ and ROP of Aggregate, 0.9831 R and 0.418 MAE and 0.9999 R and 0.1673 MAE for EOQ and ROP of Sand, and 0.9951 R and 1.6512 MAE and 0.9828 R and 6.1731 MAE for EOQ and ROP of Cement. Additionally, 63.35%, 76.47%, and 11.27% reductions have been obtained in the estimation of the optimal size of the required reservoirs for aggregate, sand, and cement respectively. Discrete Event Simulation (DES) was used to develop RMC to site delivery model. The study involved close observation of 182 concrete truck delivery cycles taken from two sample projects, which cover 50.89% of the overall yearly (2014 E.C.) concrete delivery of the case study plant. And EOQ-based ANN predictive analysis maximum consumption output results were used to get the maximum delivered amount of concrete used for the analysis of DES, the predictive output result was 1307.33 m^3. Finally, an overall simulation output result, which is optimal by assigning 8 numbers of trucks, with an overall production rate of 0.025 TL/min (10.74m^3/hr.) and 0.032 TL/min. (13.75 m^3/hr.) respectively for the truck and mixer are established.

Key Words: Ready Mixed Concrete, Inventory Control, Economic Order Quantity, Artificial Neural Network, Discrete Event Simulation.

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ABBREVIATIONS

ABC	Activity-Based Construction
ACR	Alkali-Carbonate Reaction
ANN	Artificial Neural Network
ASR	Alkali-Silica Reaction
ASTM	American Society for Testing and Materials
BIM	Building Information Modeling
BS	British Standard
CIPROS	Construction integrated project and process planning simulation system
COSYE	Construction synthetic environments
CYCLONE	Cyclic operations network
DES	Discrete-event simulation
EOQ	Economic Order Quantity
ERMCO	European Ready Mixed Concrete Organization
ES	Ethiopian Standards
GDP	Growth Domestic Product
IS	Indian Standards
JIT	Just In Time
OPC	Ordinary Portland cement
PPC	Portland Pozzolana Cement
RISim	Resource integrated simulation modeling
RMC	Ready Mixed Concrete
SABS	South African Bureau of Standards
SMC	Site Mixed Concrete
SPS	Special purpose of simulation
UK	United Kingdom
USA	United States of America

I. CHAPTER ONE – INTRODUCTION

1.1 Background of the Study

The construction industry plays a vital role in any developing country. This is mostly due to the fact that developing countries are heavily dependent on the expansion and development of their physical infrastructures, and since the construction industry is closely linked to both the social and economic sectors. As one of the developing countries, Ethiopia's construction industry has experienced considerable growth. A wide range of buildings and construction facilities are being built, including residential and commercial properties, factories, schools, hospitals, modern transportation infrastructure, and so forth. The GDP contribution of the construction industry has grown to 5.6% and approaches the Sub-Saharan average of 6% (Zewdu and Aregaw, 2015). Thus, the construction industry is a major sector of the Ethiopian economy.

In the construction industry, concrete is the most common material used to build structures. Concrete is a versatile and popular construction material in the world. It is produced by mixing fine and coarse aggregates, cement, water, and additives in a certain prescribed proportion (Dinku, 2005). In addition, admixtures are sometimes used to improve some properties of concrete; like workability and setting time. Two options are available for obtaining concrete material required in construction sites. It can be produced Site-Mixed Concrete (SMC) or Ready-Mixed Concrete (RMC). Concrete ingredients on sites are batched mostly using volume batching which necessitates a spacious area for operations. The other option is using RMC, which is manufactured in a factory or within a batching plant based on the standard required specifications, and then delivered to a worksite, by truck-mounted transit mixers.

Ready Mixed Concrete refers to concrete that is specifically manufactured for delivery to the customer’s construction site in a freshly mixed and plastic or unhardened state. Recently, RMC have a high demand in Addis Ababa since the city construction industry is growing by a high amount. Banks and other financial sectors are building high-rise buildings and road construction in the city is increasing. This resulted in the demand for a fast and quality concrete mix.

Supply chain management ensures the timely availability of the necessary resources, enabling effective management of the construction project from beginning to end. Among the several management plans in ready-mix concrete batching plants, inventory, and delivery time are the most important ones. Reducing the effect of uncertainties on delivery operations usually entails setting up material inventory to prevent interruptions, while poor inventory management will lead to waste. Therefore, an appropriate inventory control policy is essential to improve RMC delivery performance.

Ready-mix concrete is a perishable product, which involves inherent challenges to deliver a quality pour to customers. The supply chain's analysis and simulation, however, can help the construction industry's techniques to be improved. Simulation modeling of complicated, dynamic, and interactive processes in construction is essentially a computer-supported implementation of a systems approach. A system is "an integrated combination of components and activities, designed to follow a common purpose and exists to achieve a better understanding of the problem and hence help create a 'tool' to resolve the problem" (Riley and Towill. 2001). Discrete-event simulation keeps track of changes in a state of a system occurring at discrete points in time and builds a logical model of a system for experimenting on a computer. The methodology of discrete-event simulation is a general methodology that affords a means of modeling a ready-mixed concrete operation and construction systems on a stochastic basis (Zayed and Halpin 2001).

RMC is one of the aspects of the construction industry which helps to get the required quality and speed of construction, which highly demands considerable attention. However, there is a limited local study that potentially addressed the issue of RMC material inventory integrated with delivery in the case of Addis Ababa, this research is intended to fill the gap.

1.2 Statement of the Problem

Nowadays, there are mega construction projects in Ethiopia. These construction projects use a large volume of RMC, which is commonly used in construction due to its several benefits like uniformity and faster production, compared to concrete prepared by conventional methods. RMC suppliers in Addis Ababa are working on supplying RMC to satisfy the huge demand for concrete works on construction sites. It is challenging and complicated to organize and carry out these activities since they take place in a very uncertain environment. Such an event takes place on a specific process and is given a logical time. Real-world systems that may be divided into several logically distinct processes that proceed independently across time are modeled using discrete event simulation (DES). So**, i**ncorporating the Ready-mix concrete delivery operation with discrete-event simulation is one of the simulation techniques used to minimize difficulty and complexity and optimize cost and productivity. In addition to reducing the effect of uncertainties on delivery operations and determining the optimal time and quantity of an order with mathematical models, an appropriate raw material inventory control is essential.

Although the application of simulation and raw material inventory control remains a well-researched area in other countries, there is limited study on integrating raw material inventory control used for concrete production with the delivery of concrete in batching plants, particularly to estimate the required reservoirs for storage of materials based on optimal order quantity and to deliver RMC from one plant to multi-sites on time and as cost-effective as possible which necessitated this study. The presence of additional and excessive reservoirs for material increases reservoir supply costs, repair and maintenance costs, and non-optimal occupation of the plant land space. Additionally, RMC usually needs to be poured within a short time after being produced by the RMC batch plant, which limits the service area of delivery. This is why raw material inventory control integrated with the delivery simulation model is required to solve a problem related to RMC batching plant.

1.3 Objectives of the Study

1.3.1 General Objectives

The main objective of this thesis study is to identify and develop an EOQ-based ANN predictive model for raw material inventory control and delivery of RMCs to sites in Addis Ababa.

1.3.2 Specific Objectives

The specific objective of this research can be stated as follow:

- To develop an EOQ-based ANN predictive model for the prediction of the optimal ordered quantity and reordering points of RMC raw materials.
- To estimate the optimal number and volume of RMC raw material reservoirs required by using the output of the ANN predictive model.
- To develop and optimize an effective RMC to site delivery simulation model by integrating with the output of EOQ-based ANN predictive optimal ordered quantity concrete.

1.4 Research Questions

This research will answer the following questions

1. Can Artificial Neural Network (ANN) predictive model be used to predict the optimal order quantity and reordering point of raw materials based on the results of Economic Order Quantity (EOQ)?
2. Is there an effective usage of land and reservoirs for raw materials storage in the concrete batching plant?
3. Is there effective productivity and utilization of resources for the delivery of concrete to sites?

1.5 Scope and Limitation of the Study

This study focuses on the development of an integrated raw materials inventory model, with a simulation model for the delivery of RMC to sites in Addis Ababa. Generally, the study uses an EOQ inventory control model, an EOQ-based ANN predictive model using the WEKA 3.8.6 tool, and a DES model for the delivery of RMC to sites using Simphony CYCLONE software.

The scope of this study covered a selected concrete batching plant for the raw materials inventory control model and for the RMC sites delivery model one plant–to–multi-sites concrete delivery type is selected to get a representative sample project. With these study subjects in mind, two sample projects (case studies) are chosen. The sample projects are the Bole Homes – Gumruk Road project and the Sansusi – Tatek Kela Upgrading Road project as a delivery site of RMC. And a selected concrete batching plant as a plant site for the development of RMC to site delivery model.

The limitations of this study are mostly a lack of documented data. Since RMC’s supply introduction to Ethiopia's construction business was very recent, its records or history are also relatively recent. As a result, the official bodies that are involved in the topic are quite new and lack of experience with complete documentation and simulation software.

1.6 Significance of the Research

In Ethiopia, the construction industry, especially Ready-Mix concrete operation is not well researched, and this study helps the industry planners and managers in minimizing the difficulties and complexity during the planning and operation of Ready-Mix Concrete batching plant. Another significance of the study will lay a foundation for future Ready-Mix Concrete research. Furthermore, the following are some of the significance of this research:

1. This research's findings and analysis results can be used as initial benchmark information for similar projects.

2. The proposed model and its observation-based data collection format sheets can be used in assessing and inspecting the concrete delivery process in other construction sites. In addition, the proposed model can serve as a guide in material inventory control and the RMC delivery planning stage.

3. It will identify critical activity in Ready-Mix Concrete delivering operations through optimization. The finding will be helpful for the improvement of Ready-Mix Concrete batching plant operation productivity and resource utilization.

1.7 Research Organization

The following research chapters are organized around the concepts, details, and implementation of the study tasks. There are five sections in this thesis. These are:

Chapter One – Introduction

This chapter gives a brief introduction to the issues of planning material inventory control and RMC site delivery in the construction industry. In addition, it describes the statement of the problem, research objective, research question, research significance, and research scope and limitations.

Chapter Two – Literature Reviews

This chapter consists in-depth of the technique and practice of material inventory control and RMC site delivery planning with the support of computer-aided software through a literature review. The majority of the resources discussed in this chapter have already been published as technical papers and reports, books, journals, and best practices. The source material that was cited in the paper has been acknowledged.

Chapter Three – Research Design and Methods

This chapter discusses the research material and methods by describing the sample project location (case study), data sampling, data collection methods, model development, and data analysis model.

Chapter Four – Analysis and Discussion

Chapter four examines the input data analysis and the perimeters, designing and executing the simulation model, output data analysis, result, and statistic report discussion, and result in comparison to different material inventory control models in depth before summarizing the research findings.

Chapter Five – Conclusion and Recommendation

This chapter includes a conclusion and recommendations for further research and action based on the study's results and issues.

II. CHAPTER TWO - LITERATURE REVIEW

2.1 General

Concrete is one of the major construction materials in the construction industry and is considered the most economical, strong, and durable material. Concrete is produced from three basic ingredients: cement, aggregate, and water. In addition, admixtures are sometimes used to improve some properties of concrete; like workability and setting time. The ingredients of concrete should be of good quality that satisfies the requirements set in standards.

Ready Mix Concrete is produced in a controlled environment in batching plant, ingredients are standardized and well-proportioned to get the required quality of concrete. Also, it is manufactured in a factory or batching plant, according to a set recipe, and then delivered to a work site by truck-mounted transit mixers, this results in a precise mixture, allowing specialty concrete mixtures to be developed and implemented on construction sites (Sen, Amiyangshu and Shouvik, 2016).

To create an effective and efficient construction industry, the planning process plays a great role. Planning is undertaken to understand the problems and to develop a course of action. The primary objective of planning in material inventory management is to ensure that materials and components are available for production, and final products are ready for delivery. Logistics is part of the supply chain process that plans, implements, and controls the efficient flow of goods, services, and related information to fulfill customers' requirements, so efficient management of construction material planning tasks requires an integrated approach to various logistical functions (Jang et al. 2003).

To ensure material availability for production and to deliver good quality products in a well-executed manner, planners need to be able to develop models and advanced systems. The flows between the processes and resource utilization of the processes could directly affect the performance of the construction operation, computer simulation can help to predict the performance of the construction operation in terms of process flows and resource utilization (Zahran and Nassar 2013)

Given the supply chain nature of RMC production, delivery, and placement process, supply chain management concepts should be taken into consideration as tools for systematic operational planning. Developing a model to ensure effective management of construction projects in the planning phase is also necessary to maximize project productivity.

2.2 Definitions of Concrete

Concrete is a composite material made up of fine and coarse aggregates that are bonded together with a fluid cement (cement paste) that hardens (cures) over time. Concrete is the most often used building material and is the second most used substance in the world after water (Gagg, 2014). ASTM also defines concrete, as "Concrete is a composite material composed of hydraulic cement, aggregates, and water, with or without admixtures, fibers, or other cementitious components". The binder or matrix is a combination of cement and water; it is commonly called the cement paste. Aggregates are essentially filler materials that can be separated into fine and coarse aggregates. In addition to aggregates and binders, there is another material called additive which may be used in concrete to improve certain properties (George et al. 1965).

Different concrete strengths can be achieved by changing the mix proportions of these ingredients. In general, concrete is a mixture of two components: aggregates and paste. The paste binds the aggregate into a rocklike mass because of the chemical reaction between cement and water, sometimes mineral and chemical admixtures may also be included in the paste. In well-made concrete, every particle of aggregate is completely coated with paste and all of the spaces between aggregates are filled with paste (Steven et al. 2003).

Similarly, Concrete is an extremely versatile construction material. Compared with other construction materials, provided that suitable control is maintained over the selection of the constituent materials, and how they are batched and mixed, and as long as handling, placing, compaction, and curing are properly carried out, the concrete will be capable of sustaining considerable loading in demanding situations. Concrete in its fresh state is a plastic material, the flow characteristics of which can be simply controlled. Initially, the gain in strength is rapid, measured in hours, but concrete continues to harden throughout several years. Concrete can be used unreinforced in massive construction works such as dams, foundations, and similar applications.

According to George et al. (1965), in concretes the proportions of these principal components, the binder, and the aggregate are controlled by the requirement that;

1. When freshly mixed, the mass be workable or placeable.
2. When the mass is hardened, it possesses strength and durability adequate to the purpose for which it is intended.

3. The cost of the final product is a minimum consistent with acceptable quality.

2.2.1 Concrete Making-Materials

2.2.1.1 Cement

Cement is the most active constituent of concrete and commonly has the highest unit cost, hence, its selection and proper use are important in obtaining the most economical and balanced properties desired for any particular concrete mixture. In a concrete mixture, the function of the cement is to react with the water forming a plastic mass when the concrete is fresh and a solid mass when the concrete is hard. Nowadays, concrete made with Portland cement is the most used manmade material in the world. Portland cement is a finely powdered substance, usually gray or brownish grey, composed largely of artificial crystalline minerals, the most important of which are calcium and aluminum silicates (Troxel 1956). Portland cement is also commonly used in Ethiopia for concrete production since it is a reasonably inexpensive building material due to the low cost and extensive availability of the limestone, shales, and other naturally occurring elements required in its production. So, all the discussions in this paper will particularly focus on this kind of cement.

There are two processes of cement production, dry process, and wet process. In the dry process, materials are crushed, dried, and then ground in ball mills to a powder, which is burnt in its dry condition. Whereas in the wet process, the materials are first crushed and then ground to form slurry in wash mills. After passing through the wash mills and the slurry silos, the slurry passes to the slurry tanks. The slurry is next pumped to a kiln and made to the clinker at clinkering temperature of about 1400°c to 1500°c. The cement clinker then passes through clinker coolers. Having cooled sufficiently, the clinker is ground to the required degree of fineness. During grinding, gypsum, which acts as "a retarder" is incorporated (Murdook and Brook 1979).

Table 1. Approximate limits of oxide composition in cement (Duggal 2000).

Oxide	Function	Content in percent (%)
CaO	Control strength and soundness. Its deficiency reduces setting time and strength	60-67
SiO_2	Gives strength. Excess of it causes slow setting	17-25
Al_2O_3	Responsible for quick setting, if excess, it lowers the strength	3.0-8.0
Fe_2O_3	Gives color and helps infusion of different ingredients	0.5-6.0
MgO	Impart color and hardness, if excess it causes cracks in mortar and concrete and unsoundness	0.1 - 4.0
A1kalis	Those are residues, and if excess causes efflorescence and cracking	0.2 - 1.3
SO_3	Makes cement sound	1.0-3.0

Table 1. Shows the raw materials used in the production of Portland cement mixed to form compounds in the finished product. The four compounds regarded as the major constituents of cement are Tricalcium Silicate ($3CaO.SiO_2$ or C_3S), Dicalcium Silicate ($2CaO.SiO_2$ or C_2S), Tricalcium Aluminate ($3CaO.Al_2O_3$ or C_3A), and Tricalcium Aluminoferrite ($4CaO.Al_2O_3.Fe_2O_3$ or C_4AF). These compounds are different in the rate of reaction, heat liberation, and cementing value (Neville 2011).

Types of Portland cement can be varied by changing the relative extents of its conspicuous chemical compounds, by the degree of fineness of the clinker grinding, and/or by including a few pozzolanic materials. As a result, there are several types of cement for different purposes. A few of them are: - Ordinary Portland Cement (OPC), Rapid Hardening Portland cement, Sulfate Resisting Portland Cement, Low Heat Portland Cement, and Portland Pozzolana Cement (PPC). Of those Ordinary Portland cement and Portland Pozzolana Cements are produced in Ethiopia. A pozzolan is characterized in ASTM C 618 as “a siliceous or siliceous and aluminous material, which in itself has small or no cementations value but which can, in finely divided form and within the presence of moisture, chemically react with calcium hydroxide at ordinary temperatures to make compounds having cementations properties.” Pozzolanic material can be used to modify and improve the plastic and hardened properties of concrete. In Ethiopia, calcite types and volcanic soil pozzolanic materials are found near Zeway and between Wolenchite and Metehara, and their analyses and chemical compositions were done by researchers in the laboratory (Mengistu 2010).

2.2.1.2 Aggregate

Aggregates, such as gravel, crushed stone, and sand, are raw materials produced from natural sources and mined from pits and quarries. They are used to make compound materials like asphalt concrete and Portland cement concrete when combined with a binding medium like water, cement, or asphalt. Because aggregates account for 60 percent to 75 percent of the concrete volume (70 percent to 85 percent by mass), they have a considerable impact on the concrete's freshly mixed and hardened properties, mixture proportions, and economy (Duggal 2000). Certain aggregate qualities that affect the paste required of fresh concrete, including form and texture, size gradation, moisture content, specific gravity, and bulk unit weight, must be known to proportion suitable concrete mixtures (Steven et al. 2003).

Furthermore, aggregates account for the majority of the volume of concrete. As a result, it has a major impact on concrete quality, particularly strength. This is because excellent aggregates are known to have higher crushing strength and impact resistance. Aggregates affect not only the strength of concrete but also the durability and structural performance of concrete (Gambhir 2002). Aggregate qualities like size and shape have an impact on the durability and structural performance of concrete. Because flaky particles tend to be oriented in one plane, bleeding water, and air gaps form underneath elongated and flaky particles can hurt concrete durability (Neville (2011).

When selecting aggregate for usage in a certain concrete, three crucial requirements should be taken into account according to (Mikyas (1987).

1. **Workability**-when fresh for which the size and gradation of the aggregate should be such that undue labor in mixing and placing will not be required.
2. **Strength and durability**-when hardened for which the aggregate should be:
    - **a.** Be stronger than the required concrete strength
    - **b.** Contain no impurities which adversely affect strength and durability
    - **c.** not go into undesirable reactions with the cement
    - **d.** Be resistant to weathering action
3. **Economy of the mixture**–meaning says that the aggregate should be:
    - **a.** Available from local and easily accessible deposit or quarry
    - **b.** Well graded to minimize paste hence cement requirement

2.2.1.2.1 Origin and Classification of Aggregate

Depending on their origins, aggregates can be characterized as natural or artificial. Natural aggregates come from quarries where crushed rocks are processed or from riverbeds, whereas artificial aggregates come from industrial byproducts like blast furnace slag. Natural aggregates are the most prevalent and are important for the Ethiopian building industry because artificial aggregates are rarely created **(**Dinku, 2005).

Aggregate physical and mechanical properties are inherited from parent materials, while the parent material's attributes are determined by its geological development. Igneous, sedimentary, and metamorphic rocks are the three major divisions of geological rocks based on their origin. Igneous rocks are generated when molten matter (magma) solidifies either at or below the earth's surface. Igneous rocks are classified as plutonic or intrusive (those that cooled slowly within the earth, such as granite, diorite, gabbro, and others) or volcanic or extrusive (those created from quickly cooled lava) (e.g., volcanic rock, volcanic glass, felsite, basalt, etc.). Plutonic rocks have grain sizes greater than 1mm and are categorized as coarse or medium-grained, whereas volcanic rocks have grain sizes less than 1mm and are classified as fine-grained, and are not visible to the naked eye (Dinku, 2005).

As a result of sedimentation from disintegrating products, sedimentary rocks are created as strata. They are stratified rocks that are usually created underwater but can also be formed by wind and glacial action. During the geologic time, the sediments are cemented together or compacted to varying degrees. Sandstone, limestone, and shale are common examples. Metamorphic rocks, on the other hand, are generated by the impact of heat, pressure, or both on pre-existing igneous, sedimentary, and metamorphic rocks. Textural, structural, or mineralogical alterations may be present, as well as chemical composition changes. Marble, meta-quartzite, and slate are examples of common minerals.

Basalt, trachyte, and ignimbrite are the most frequent aggregate rocks found in and around Addis Ababa. Basalt is a fine-grained extrusive rock with a relatively low glass concentration (Dinku, 2005).

2.2.1.2.2 Properties of Aggregate

Most properties of aggregate depend on the properties of the parent rock e.g., chemical and mineral composition, specific gravity, hardness, strength, physical and chemical stability, pore structure, color, etc. Every property can have a significant impact on the quality of fresh or hardened concrete (Neville and Brooks 2010). Shape and texture, size gradation, moisture content, specific gravity, and bulk unit weight are all key factors to consider when proportioning concrete mixes.

The physical properties like specific gravity, porosity, thermal behavior, and chemical properties of an aggregate are attributed to the parent material. The shape, size, and surface texture are essential for concrete workability and bond characteristics between the aggregate and cement paste. It is, therefore, essential to understanding the mechanical, physical, and chemical properties of aggregate (Dinku, 2005).

I. Physical Properties

Specific gravity, porosity, absorption capacity, moisture content, unsoundness due to volume changes, and thermal characteristics are all physical parameters of aggregates that need scrutiny.

A. Aggregate Size, Shape, and Surface Texture

The usage of a larger aggregate maximum size has numerous effects on the strength. First, because larger aggregates have a lower specific surface area and the aggregate–paste bond strength is lesser, aggregate fails along the surfaces of aggregates, resulting in lower concrete compressive strength; second, for a given volume of concrete, using larger aggregate results in a smaller volume of paste, which provides more restraint to paste volume changes. This may cause additional stresses in the paste, resulting in micro-cracks, which could be a key component in very high-strength concretes (Neville 2011). As a result, it makes sense to use smaller size aggregates to make higher-strength concrete.

Freshly mixed concrete's properties are more influenced by particle shape and surface texture than cured concrete's qualities. When compared to smooth, rounded, and compact aggregate, rough-textured, angular, and elongated material requires more water to generate workable concrete. As a result, to maintain the water-cement ratio, the cement content must also be raised. Flat and elongated particles are generally avoided, or their weight is limited to around 15% of the overall aggregate weight. The most important criterion for a concrete aggregate is that it stays stable within the concrete and in the specific environment throughout the duration of the concrete's design life, without compromising the concrete's performance in either the fresh or hardened condition (Dinku, 2005).

The particle shape of crushed aggregate is determined not only by the nature of the parent material, but also by the type of crusher and its reduction ratio, or the ratio of the material fed into the crusher to the completed product size (Neville 2011). The strength, abrasion resistance, and degree of wear to which natural aggregates have been exposed in their depositional environment determine their shape. Natural aggregates have a spherical shape and are less angular. The shape of manufactured aggregate, on the other hand, is determined by the rock type and the crushing equipment used. When compared to natural aggregates, manufactured aggregates are more angular.

For a given workability, the rounder aggregate uses less water and cement paste (Gambhir 2002). The amount of mixing water used could be lowered by 5 to 10%, and the sand content could be reduced by 3 to 5%. Crushed aggregate, on the other hand, may result in a 10 to 20% increase in compressive strength due to the establishment of a stronger aggregate mortar bond. For concrete with a water-cement ratio of less than 0.4, this increase in strength can be up to 38 percent. The workability is significantly reduced by the elongated and flaky particles, which have a larger surface area to volume ratio. With water and air spaces underneath, these particles tend to be orientated in one plane. An aggregate with a rough and porous texture is preferable over one with a smooth surface since the former can strengthen the aggregate-cement bond by 75%, resulting in a 20% increase in compressive and flexural strength (Neville 2011).

II. Mechanical Properties

Mechanical properties, in particular, are physical characteristics of a substance that describe how it reacts when subjected to external loads. These qualities are not constant; rather, they vary with temperature, loading rate, and other factors. Aggregates for concrete should have mechanical qualities that are in line with the recommendations of the standard. The mechanical properties of aggregate include compressive strength, hardness, and toughness.

The compressive strength of aggregates is determined by their greatest strength when compressed. It's important to note that crushed stones are made by smashing big rocks. As a result, aggregates are intrinsic materials, and their compressive strength is largely determined by the type of crushed rock (for coarse aggregates). The resistance of a material to abrasion or scratching is measured by its hardness. In other words, a material's hardness is manifested when it is loaded in the plastic zone and gives localized resistance to plastic deformation. When a material is loaded in increments, it begins to distort plastically after a certain load. Toughness refers to a material's capacity to sustain loading by deforming in the plastic range without fracture or failure.

III. Chemical Properties: Alkali-Aggregate Reactions

The term "alkali-aggregate reaction" refers to a reaction in concrete that happens over time between certain active mineral constituents often present in some aggregates and the sodium and potassium alkali hydroxides from Portland cement paste. This reaction can cause the changed aggregate to expand, resulting in concrete spalling and a loss of strength.

There are two types of alkali-aggregate reactions: alkali-silica reaction (ASR) and alkali-carbonate reaction (ACR). The alkali-silica reaction occurs when alkali hydroxide in Portland cement reacts with siliceous rocks and minerals such as opal, chert, and chalcedony in aggregates. The results of this reaction frequently cause severe concrete expansion and cracking, as well as the breakdown of the concrete structure. The alkali-carbonate reaction, on the other hand, occurs when cement hydroxides react with certain dolomitic limestone aggregates, and it can cause undesirable expansion. Because aggregates containing reactive silica minerals are more abundant, the alkali-silica reaction is of more concern than the alkali-carbonate reaction. Alkali reactive carbonate aggregates have a specific composition whose occurrence is relatively rare (Sydney, M.F. et al 2003). Because dolomitic limestone is so uncommon in Ethiopia, more focus should be placed on alkali-silica interactions.

Almost all aggregates used in Ethiopian construction are of natural origin. Except for scoria sources, the bulk of coarse aggregate sources in Addis Ababa is found near rivers within the city. The main suppliers of aggregates to Addis Ababa are the large riverbanks of the Akaki River and the Matahara River (near Bole AirPort). Scoria is mined on flat or rolling terrain from large mountains. Quarry sites are being built on the fringes of the city in places that were previously uninhabited (Dinku, 2005).

2.2.1.3 Water

The goal of utilizing water with cement is to cause the cement to hydrate. More water than is required for hydration acts as a lubricant between the coarse and fine particles, resulting in workable and cost-effective concrete (Duggal 2000). Aside from that, water is utilized to wash aggregates and curing.

When mixing water for concrete, almost any natural water that is drinkable and has no pronounced taste or odor can be utilized. Salt, oil, industrial wastes, alkalis, sulphate, organic debris, silt, sewage, and other impurities in the water can be dangerous if present in large proportions. Such impurities would be detected by testing using the senses of smell, sight, and taste; however, the water of questionable quality should be sent to a laboratory for analysis and tests (Mikyas 1987).

According to Ethiopian Standard ES 2310:2005 water used for concrete shall fulfill the chemical requirements listed in Table 2 below for chlorides, sulfates and alkalis, and other harmful contamination (sugar, phosphates, nitrates, lead, and zinc).

Table 2. Chemical requirements of water used for concrete (Zahran and Nassar 2013).

Chemicals	mg/l
Maximum Chloride content	
✓ used for prestressed concrete or grout	500
✓ concrete with reinforcement or embedded metal	1000
✓ concrete without reinforcement or embedded metal	4500
Maximum Sulphates content	2000
Maximum Alkalis (sodium oxide content)	1500
Harmful contamination (maximum)	
✓ sugar	100
✓ phosphates expressed as P_2O_5	100
✓ nitrates expressed as NO_3^-	500
✓ lead expressed as Pb^{2+}	100
✓ zinc expressed as Zn^{2+}	100

Generally, Water with a pH value of 6 to 8 is considered appropriate for concrete construction. Water that is suitable for drinking is also suitable for concrete production. To produce the high-quality concrete necessary for work, the amount of water used must be restricted. Excess water, for example, weakens the link between consecutive concrete lifts, produces honeycombed concrete, and makes concrete porous. On the other side, less water makes working with concrete more difficult (Neville 2011).

2.2.1.4 Admixtures

Admixtures are those ingredients in concrete other than Portland cement, water, and aggregates that are added to the mixture immediately before or during mixing to modify one or more of the properties of concrete in the plastic or hardened state. The following are some of the different types of admixtures:

a. ***Accelerating Admixtures:*** It accelerates the setting and early strength development of concrete. It is mainly used in cold weather concreting.
b. ***Retarding admixtures:*** It expands the setting time of concrete. It is mainly used in hot weather concreting.
c. ***Air-entraining admixtures:*** Improve durability in freeze-thaw and deicer environments.
d. ***Super plasticizing admixtures:*** it is used to significantly reduce the water content ratio and to increase the flowability of concrete while maintaining workability and gaining high strength.
e. ***Water-reducing admixtures:*** This reduces the amount of water without affecting the workability of concrete.

The effectiveness of an admixture depends upon factors such as type, brand, and amount of cementing materials; water content; aggregate shape, gradation, and proportions; mixing time; slump; and temperature of the concrete.

In RMC Plant admixtures mainly perform the following functions (Mahajan and Buthello 2015).

- Reducing water content and hence increasing strength.
- Increasing durability of concrete.
- Accelerating and decreasing the setting time of concrete.
- Avoiding segregation and bleeding in concrete.
- Increasing pump ability of concrete.

Ethiopia is barely two decades into using and practicing admixtures, therefore it is still in its early stages. When compared to developed countries, the country's market availability and admixture usage are quite low. This can be the result of the product's recent release on the market and a general ignorance of the value and application of admixtures. Currently, a small number of businesses produce and import admixture from many nations across the world, including South Africa, Saudi Arabia, Germany, and Great Britain, to distribute it. The capital city of Addis Ababa is where most of the suppliers are situated. Mostly super plasticizing admixtures and water-reducing admixtures are practiced locally in the Ready Mixed Concrete batching plant, to gain high-strength concrete by not affecting the workability of concrete.

2.3 Ready-mix Concrete

"Ready-Mix Concrete" has nearly identical definitions in different literature. Ready-mixed concrete, for example, is defined by ASTM as "concrete manufactured and delivered to a purchaser in a fresh state." (ASTM, 1999). RMC, according to Yogesh, is concrete produced at a central batching plant and delivered to the job site through truck-mounted Transit Mixers (TM) (Yogesh 2016). RMC is a composite material that, like all well-designed composites, has resultant properties that combine the best qualities of the component materials (Dewar 1992)., as well as concrete that is specifically manufactured for delivery to the customer's construction site by truck-mounted transit mixers in a freshly mixed, plastic or unhardened state.

Therefore, Ready-mix concrete (RMC) is a type of concrete that is mixed in a central plant and transported to the construction site rather than being mixed on the job site. Every batch of RMC is created to order, according to the customer's specifications. The custom-mixed concrete is then transported to the job site in rotating drum mixers placed atop trucks.

Ready Mix Concrete (RMC) is divided into three categories based on how materials are mixed (L1Supply (Ed.). (2018).

a. ***Transit mixed Concrete:*** This is also known as Truck mixed concrete because all the ingredients are batched at a central plant and are completely mixed in the drum-mounted truck during the transit. This type of transit-mixing separates the water from the cement and aggregates, allowing the concrete to be mixed right before it is placed on the job site.
Advantage: The issues of early hardening and slump loss that cause transportation delays are avoided by transit mixing.
Disadvantage: Cement balling is a significant disadvantage of transit mixed concrete.

b. ***Shrink mixed concrete:*** The concrete is partially mixed at the central plant before being unloaded into the truck's rotating drum, where the remaining mixing takes place. The concrete is normally partially mixed at the central plant with a stationary, plant-mounted mixer to reduce or shrink the volume of the mixture, hence the name shrink mixed concrete.

Advantage: Shrink mixed concrete is typically utilized to improve the truck's load capacity and yet retain the advantages of transit mixed concrete.

Disadvantage: To establish how much mixing the drum mixer needs, there are numerous tests.

c. ***Central mixed concrete:*** Before being released into the truck mixer, the ingredients are combined in a stationary mixer. When the concrete is centrally mixed, the truck mixer is used to stir the water and ingredients.

Advantage: Central mixed concrete speeds up the batching process while also reducing the wear and tear on the revolving drum mixers installed on the trucks.

Disadvantage: Central mixed plants, on the other hand, are normally more expensive to buy and maintain than transit mixed plants.

In Addis Ababa, Ethiopia, the majority of batching factories made use of centrally mixed concrete. The various parts of this product are first loaded into a stationary mixer at the concrete plant. It is thoroughly blended there in that mixer plant. The ready-mix concrete truck will then bring the finished product to the job site after it has been properly mixed. Of course, that truck's drum mixer will rotate while it is in motion to prevent the mix from settling and to prevent the various components of the concrete from separating.

Approximately 20% of concrete plants nationwide use central mixed concrete, according to the National Ready Mixed Concrete Association (NRMCA). The trade association also highlights the following benefits of this production technique:

- Compared to transit-mixed (or truck-mixed) concrete, faster manufacturing
- Increased consistency and quality assurance
- Less wear and tear on the drum of the ready-mix truck

2.3.1 Historical Aspect of RMC

Ready-mixed concrete was initially invented in Germany in 1903, but the technology for transporting it had not progressed far enough by that time to make the concept commercially viable. In Baltimore, Maryland, the first commercial supply of RMC was made in 1913, and in 1926, the first rotating drum-type transit mixer was born, with a significantly lesser capacity than those available today (Dewar, J. 1992). RMC was first introduced in certain European countries in the late 1920s and 1930s.

The first plants had a fairly limited capacity. In 1931, a ready-mixed concrete plant was built on the site of what is now Heathrow Airport in London, with a 1.52 m^3 (2 yd^3) central mixer and six 1.33 m^3 (1 3/4 yd^3) capacity agitators, with a total output of 30.58 m^3/hr. (40 yd^3/hr.). Aggregates were kept in a four-compartment bin with a capacity of 76.45 m^3 (100 yd^3). Cement was manually handled in bags. There were just six enterprises in the UK producing RMC at the start of World War II. Following WWII, the RMC industry in Europe, particularly the United Kingdom, had a boom. There were as many as 1,100 RMC plants in the UK in the mid-1990s, consuming around 45 percent of the cement produced there (ERMCO statistics, 2013) As of 2013, there were 5,850 companies in Europe with a total production of 349.4 million m3 of RMC, with a cement consumption of 60.8 percent of total cement sales.

Only 5% of cement manufactured in the United States was used through the RMC technique until 1933. In the United States, the sector has progressed steadily. From 1950 to 1975, the RMC industry utilized 1/3 to 2/3 of the total OPC consumed in the United States, and by 1990, this consumption had risen to 72.4 percent of the total OPC consumed in the country. In 1978, there were up to 5,000 RMC firms in the country. However, by 1994, the number had dropped to 3,700, with only 6 to 7% of the companies controlling nearly half of the RMC market. According to Gaynor, the industry's technical sophistication has increased as a result of the market's consolidation. RMC manufacturing in the United States increased in 2013 (Gaynor, R. D. 1978). In 2013, 115 million m^3 RMCs were produced in the United States.

The first RMC facility was established in Japan in 1949. Dump trucks were initially used to transport low-consistency concrete for road building. Mixing-type truck mixers were launched in the early 1950s, and the industry in that country has grown exponentially since then. By 1973, Japan had 3,413 RMC plants, which had increased to 4,462 by the end of the 1980s. By 1992, Japan had become the world's largest producer of RMC, manufacturing 181.96 million tons per year (Takeyama. M. 1996). Japan produced 86 million m^3 of concrete in 2013.

Unlike Ethiopia, where concrete is often created on-site, most developed and developing countries rely on RMC production plants to generate the majority of the total concrete produced in their countries. RMC now provides high-tech solutions to the construction industry's needs. It enables the construction of longer bridges, taller skyscrapers, tunnels, dams, and other structures.

2.3.2 Components of RMC Batching Operation and Production Process

A concrete batching plant, also known as a batch plant or a batching plant, is a device that combines different ingredients such as cement, sand, water, and other additives to produce concrete. The process of weighing and inserting ingredients into the mixer to make a batch of concrete is known as batching. Concrete is one of the most durable materials used in construction projects such as bridges, houses, highways, walkways, and other structures.

The parts and accessories of the concrete batching plant work together to produce high-quality concrete. It is necessary to understand the many components of a concrete batching plant to comprehend the plant's functioning concept.

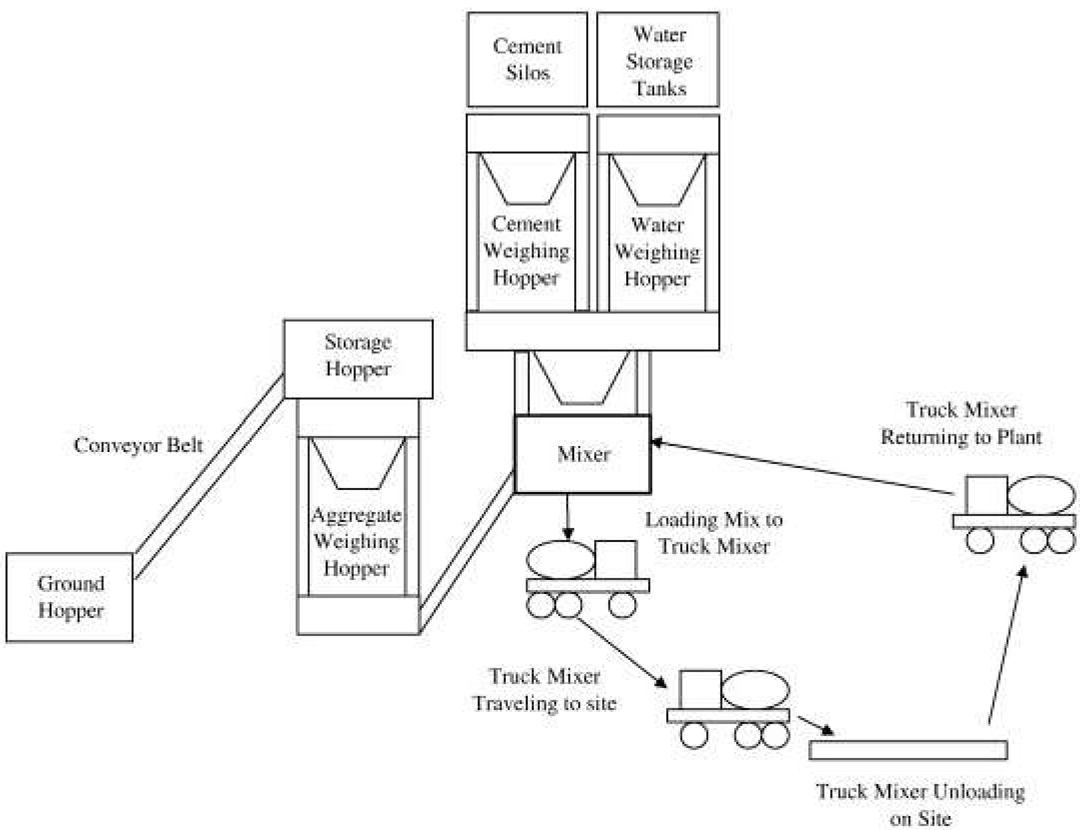


Figure 1: RMC supply process (Park and Lee 2011).

Figure 1, shows a schematic diagram for the RMC supply process starting from the batching plant concrete production up to the delivery of concrete to sites, and the detailed explanation for each term shown in the figure is discussed below.

2.3.2.1 Ground Hopper

The storage hopper is connected to the hopper, which is situated on the ground, via a conveyor belt. An operator operates the vehicle that transports aggregates and sand to the ground hopper. The items are then transported to the storage hopper through the conveyer belt.

2.3.2.2 Storage Hopper

Sand and aggregates are stored in compartments in the storage hopper. Materials are discharged into the aggregate weighing hopper, which lies directly below the storage hopper when they are released.

2.3.2.3 Cement Silo and Water Storage Tank

Cement silos and water storage tanks are placed above the mixer. Cement is released into a weighing hopper, which weighs it. The cement is then gravity-fed into the mixer. Water is also fed into the mixer via the water-weighing hopper.

2.3.2.4 Weighing Hopper

Weighing hoppers are divided into three types. The weighing hoppers for cement and water are positioned above the mixer, and below the cement silos and water tanks. After weighing, the cement and water are discharged straight into the mixer due to gravity. On the other hand, the aggregate weighing hopper weighs sand and aggregates before transporting them to the mixer via a conveyor belt.

2.3.2.5 Mixer

All of the ingredients for batching ready-mixed concrete are delivered to the mixer. The mixer ensures that the components are combined evenly and thoroughly to the desired workability by rotating continuously. The batch plant control room operator uses an amp-meter to evaluate whether the mix is too dry or too wet and then makes the required adjustments before releasing it to the truck mixers.

The ready-mix concrete production process should pass through the following process Batching, Mixing, Transporting, and Placing.

***Batching**:* is the process of weighing or measuring concrete mix materials and putting them into the mixer. To make concrete of consistent quality, the ingredients must be precisely measured for each batch.

Mixing: It is the process of properly combining all ingredients until they are uniformly distributed and the mixture appears homogeneous. Mixers should not be loaded above their rated capacities and should be used at the manufacturer's recommended mixing speed.

Transporting and Placing: It is the process of transporting and placing freshly mixed concrete within the specified quality and time by employing various equipment and machinery.

2.4 Supply Chain Management in Construction

Supply chain management originated and flourished in the manufacturing industry. Toyota Motor Corporation was the first to use it, and it was a huge success in terms of quality, reliability, and productivity.

Different Literature has provided various definitions of supply chain management, including the following: "Supply chain is the network of facilities and distribution options that performs the functions of procurement of materials, transformations of these materials into intermediate and finished products, and the distribution of these finished products to customers" (Ganeshan and Harrison 2002). Another definition provided by (the committee on Supply Chain Integration) is "an association of customers and suppliers who, working together yet in their own best interests, buy, convert, distribute, and sell goods and services among themselves resulting in the creation of a specific end product".

Supply chain management has been used in the construction industry because of its value. Construction companies are facing rising competition, and customers are demanding cheaper costs, higher quality, quicker execution times, and more reliable schedules (O"Brien et al. 2009). To address their adversarial inter-organizational purchaser-supplier interactions and fragmented processes, a growing number of construction industry pioneers are looking into supply chain management in construction performance (Saad et al. 2002).

The goals of supply chain management in construction are to achieve an optimal supply chain configuration, reduce non-value-adding activities, make better decisions, and lower supply chain costs (O‟Brien et al. 2009). Supply chain management can achieve these goals in the following ways (Vrijhoef and Koskela 2000):

1. Improve the interface between site activities and the supply chain.
2. Improve the supply chain.
3. Transfer activities from the site to the supply chain, and
4. Integrate the site and supply chain.

According to Vrijhoef and Koskela (2000), there are alternative supply chain management concepts. First, there are supply chain management development challenges, such as order information transparency, variability reduction, material flow synchronization, essential resource management, and supply chain configuration. Second, there are supply chain management techniques such as establishing a solid partnership, modular component outsourcing, design for production, flexible manufacturing technologies, supply chain evolution with the product life cycle, and information gathering and sharing. Third, there are different levels of supply chain management, such as initial collaboration (e.g., creating excellent relationships with suppliers and distributors), logistic management, and so on (e.g., implementing and controlling the flow involving all actors in the chain). Implementing the supply chain approach could help construction companies improve their efficiency, which is often plagued by schedule and cost overruns, quality issues, and poor health and safety. The application of Supply Chain Management is not limited to the building; it can also be applied to the manufacturing and delivery of materials.

Supply chain management incorporates planning, manufacturing, and operation management necessary to bring a product to the marketplace, from the sourcing material to the delivery of the completed product. So, understanding and implementing the concept of logistic management is essential in the supply chain management of construction.

Logistic Management. The combination of processes, systems, and organizations that regulate the transfer of goods from suppliers to a pleased client without waste is referred to as a logistic system (Tan. 2001). Inventory management, vendor relationships, transportation, distribution, warehousing, and delivery services are all part of a logistics system. A Just-In-Time system, entails precise coordination with suppliers to ensure that raw materials arrive at the exact time that manufacturing is set to start, but not earlier. The objective is to hold the least amount of inventory necessary to meet demand. That means merchandise must be refilled fast and delivered where and when it is needed in smaller lot sizes.

2.4.1 Ready-Mixed Concrete Supply Chain Management

Given the supply chain aspect of RMC production, delivery, and placement process, supply chain management ideas should be taken into consideration as instruments for systematic operational planning.

Supply Chain Management is critical in the production of ready-mix concrete to assure the quality of materials, products, supplier relationships, and customer satisfaction. Material logistics planning is a decision process for strategically managing the procurement, movement, and storage of raw materials, finished product inventory, and related information flows throughout the organization and its marketing channels in such a way that current and future profitability is maximized by cost-effective order fulfillment (Martin. 1992). Concrete has its own time to set and harden, due to this problem, the batching and delivery of the ready-mix concrete is a typical example of a Just-In-Time construction system.

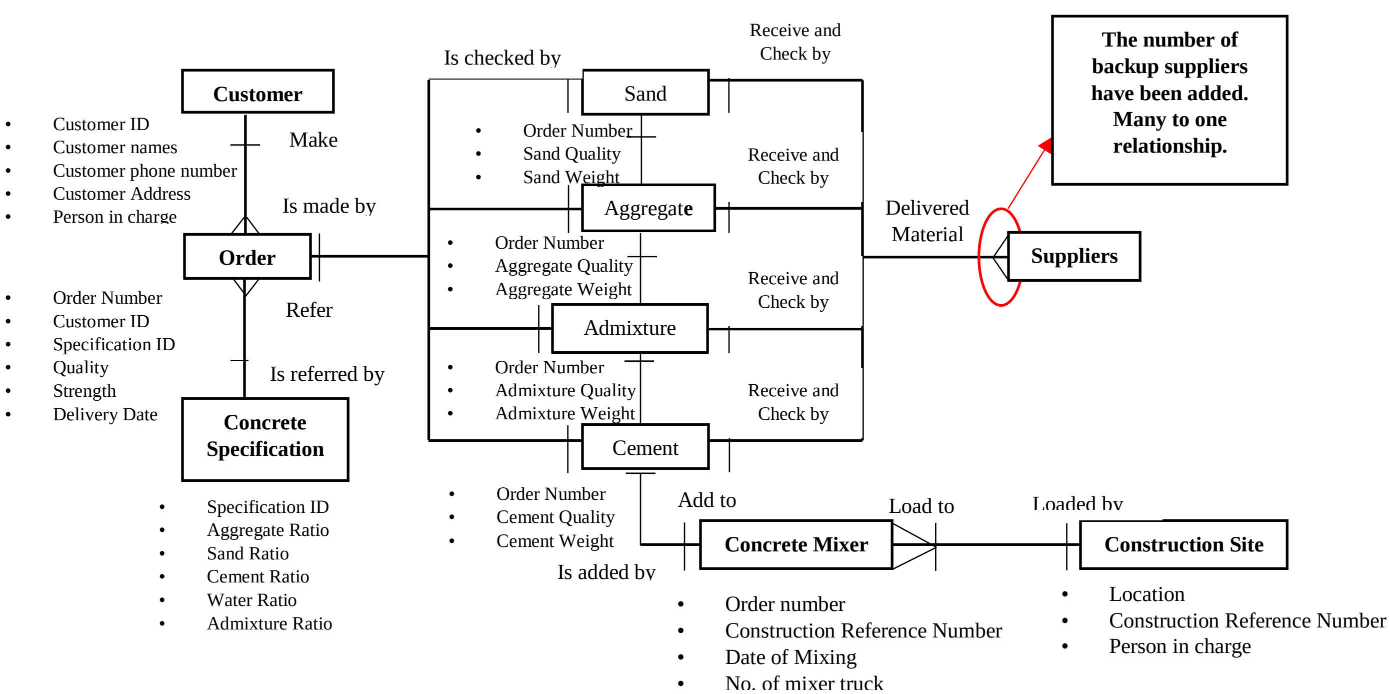


Figure 2: Theoretical Framework for the production and delivery process of ready mixed concrete (Omar. 2016).

Figure 2. Illustrates the theoretical framework for the production and delivery of ready-mixed concrete developed by (Omar. 2016) and describes the methods of obtaining cement, additive, aggregate, and sand from only one provider. If there was a problem with the supply, they had no backup supplier. For instance, the supplier may be unable to supply raw materials because of a specific issue. As a result, a new improvised research framework was created by including a backup provider for each raw material in the supply chain. Doing so can reduce the risk associated with the delivery of materials.

The production growth of Ready-Mixed Concrete in Ethiopia, especially in the city of Addis Ababa is growing because the scale of construction in Addis Ababa has created a demand for a large volume of building materials, especially concrete. Thus, it is easy for the contractors to use Ready-Mixed Concrete to speed up the time of construction because it is a readily usable product. Following that again Instead of being mixed on site, ready mix concrete is prepared specifically to the client's specifications and mixed at a plant before being supplied to the client. This implies that there is no waiting for the concrete to mix. Because the concrete is customized for the client, only precise measurements are used, which results in minimal material waste and lower concrete costs. However considerable attention should have to be given, and it is important to study the existing supply chain management of Ready-Mixed Concrete to ensure there is no wastage and problems arise within the process of production and transportation of the product to the construction site.

2.4.2 Inventory Theory

Keeping an inventory (stock of goods) for future sale or use is common in business. To meet demand on time, companies must keep a stock of goods awaiting sale. Inventory theory aims to determine rules that management can use to minimize the costs associated with maintaining inventory and meeting customer demand. Inventory is studied to help companies save money. Inventory models answer the questions:

1. When should an order be placed for a product?
2. How large should each order be?

The answers to these questions are collectively called an inventory policy. Companies save money by formulating mathematical models describing the inventory system and then proceeding to derive an optimal inventory policy. They use scientific inventory management comprising the following steps (Hillier et al. 1995):

1. Formulate a mathematical model describing the behavior of the inventory system.
2. Seek an optimal inventory policy concerning this model.
3. Use a computerized information processing system to maintain a record of the current inventory levels.
4. Using this record of current inventory levels, apply the optimal inventory policy to signal when and how much to replenish inventory.

The mathematical inventory models used with this approach can be divided into two broad categories deterministic models and stochastic models according to the predictability of demand involved. The demand for a product in inventory is the number of units that will need to be withdrawn from inventory for some use (e.g., sales) during a specific period. If the demand in future periods can be forecast with considerable precision, it is reasonable to use an inventory policy that assumes that all forecasts will always be completely accurate. This is the case of known demand where a deterministic inventory model would be used. However, when demand cannot be predicted very well, it becomes necessary to use a stochastic inventory model where the demand in any period is a random variable rather than a known constant (Hillier et al. 1995).

Because inventory policies affect profitability, the choice among policies depends upon their relative profitability. Some of the costs that determine this profitability are;

1. ***The cost of ordering or manufacturing the product***
2. ***The holding cost (sometimes called the storage cost):*** represents all the costs associated with the storage of the inventory until it is sold or used. Included is the cost of capital tied up, space, insurance, protection, and taxes attributed to storage.
3. ***The shortage cost (sometimes called the unsatisfied demand cost):*** is incurred when the amount of the commodity required (demand) exceeds the available stock.
4. ***Revenues:*** These costs may or may not be included in the model. If the loss of revenue is neglected in the model, it must be included in the shortage cost when the sale is lost.

5. ***Salvage costs:*** The cost associated with selling an item at a discounted price.
6. ***Discount rates:*** This deals with the time value of money. A firm could be spending its money on other things, such as investments.

ABC Analysis, Inventory Production Quantity, and Economic Order Quantity (EOQ) are three of the most often used inventory control models. To determine how much inventory you should have on hand, each inventory model takes a different technique.

I. ABC Analysis

The more money a certain item of inventory gives you, the more valuable that item is to you. Your inventory is categorized based on levels of relevance using ABC analysis. You are aware of where to direct your attention by understanding which inventory is the most crucial. The Just in Time method and other inventory management techniques are commonly combined to maximize the effectiveness of ABC Analysis. Inventory is divided into three groups: A, B, and C. The Pareto Principle, popularly known as the 80/20 rule, serves as its foundation.

Using the Pareto Principle

Category A: Inventory in this category earns the greatest money while accounting for a small amount of your total inventory. This is the top-of-the-line stock you have. Only 20% of your inventory is used for it, but it generates 70% of your overall revenue. Category A inventory is given the most care and has strict ordering restrictions in place.

Category B: Unlike Category A inventory, Class B inventory is not critical to the survival of your company, but it is nonetheless important. It represents 30% of your stock and 25% of your revenue.

Category C: inventory represents 50% of your products with 5% income. Although this inventory doesn't yield as much profit as A and B, it is reliable. Since it generates such a small amount of revenue, inventory controls are fairly loose in this situation.

II. Inventory Production Quantity

This inventory control approach, also known as Economic Production Quantity, or EPQ, instructs you on how many items to order for your company in a single batch to cut down on setup and holding expenses. It is based on the supposition that each order is delivered to your company by your supplier in pieces rather than as a whole product. The EOQ concept is expanded upon in this model. The difference between the two models is that the EOQ model implies suppliers deliver inventory in whole to your client or business.

III. Economic Order Quantity (EOQ)

One of the earliest and most well-liked inventory management techniques is Economic Order Quantity. Based on your company's holding costs, ordering costs, and rate of demand, EOQ tells you how many inventory units to order to cut expenses.

The most common inventory situation faced by manufacturers, retailers, and wholesalers is that stock levels are depleted over time and then are replenished by the arrival of a batch of new units. A simple model representing this situation is the economic order quantity (EOQ). (Hillier et al. 1995).

Units of the product under consideration are assumed to be withdrawn from inventory continuously at a known constant rate, denoted by a; that is, the demand is a unit per unit of time. It is further assumed that inventory is replenished when needed by ordering (through either purchasing or producing) a batch of fixed-size (Q units), where all Q units arrive simultaneously at the desired time. For the basic EOQ model to be presented first, the only costs to be considered are

K = setup cost for ordering one batch,

c = unit cost for producing or purchasing each unit, and

h = holding cost per unit of time held in inventory.

The objective is to determine when and by how much to replenish inventory to minimize the sum of these costs per unit of time (Hillier et al. 1995).

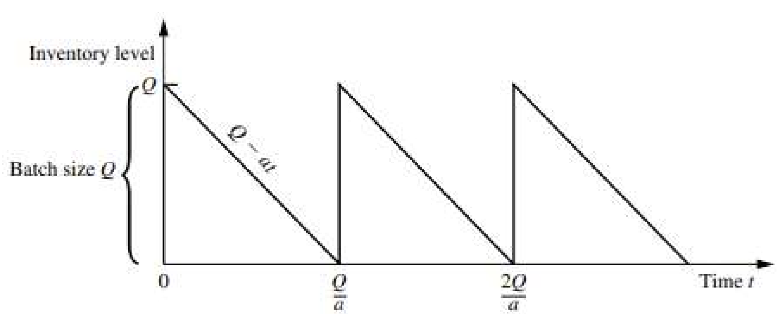


Figure 3: Diagram of inventory level as a function of time for the basic EOQ model (Hillier et al. 1995).

Assumptions (Basic EOQ Model).

1. A known constant demand rate of a unit per unit of time
2. Order quantity Q arrives when the inventory level drops to zero
3. Purchase cost per unit is constant (no quantity discount)
4. Delivery time (lead time) is constant
5. Planned shortages are not permitted

Regarding assumption 2, there usually is a lag between when an order is placed and when it arrives in inventory. The amount of time between the placement of an order and its receipt is referred to as the lead time. The inventory level at which the order is placed is called the reorder point.

The total cost per unit time T is obtained from the following components.

Production or ordering cost per cycle = $K + cQ$

The average inventory level during a cycle is $(Q + 0)/2$ = $Q/2$ units, and the corresponding cost is $hQ/2$ per unit of time. Because the cycle length is Q/a,

Holding cost per cycle = $\frac{hQ^2}{2a}$,

Total cost per cycle = $K + cQ + \frac{hQ^2}{2a}$,

So the total cost per unit of time is

$$T = \frac{K+cQ+(hQ\text{^}2)/2a}{2a} = \frac{aK}{\mathrm{Q}} + ac + \frac{hQ}{2}$$

The value of Q, say Q*, that minimizes T is found by setting the first derivative to zero (and noting that the second derivative is positive).

$$\frac{dT}{dQ} = -\frac{aK}{Q^2} + \frac{h}{2} = 0,$$

$$Q^* = \sqrt{\frac{2aK}{h}} \qquad \text{(Eqn. 1)}$$

Which is the well-known EOQ formula. The corresponding cycle time, say t*, is

$$t^* = \frac{Q^*}{a} = \sqrt{\frac{2K}{ah}} \qquad \text{(Eqn. 2)}$$

2.5 Application of Artificial Neural Networks in the Construction Industry

The construction industry has contributed significantly to the development and maintenance of buildings and civil infrastructure. The construction industry is a sector that generates a lot of data, and its data volume is increasing at an unprecedented rate (You and Wu. 2019). For the adoption of suitable construction methods to enhance project performance, the hidden knowledge in these data is of significant relevance. In the meanwhile, data in the construction sector are still not adequately exploited. Machine learning, a collection of technologies that can automatically find patterns in data, significantly improves efficiency and makes the most of computing power, especially when processing massive amounts of data (Yx and Ying. 2021). In numerous, constantly growing construction-related fields, it has demonstrated great performance. To handle the exponential development in data generation in construction management, intelligent technology is urgently needed, with artificial neural networks (ANN) being one of the most promising ones.

Artificial neural networks (ANNs) or conduction systems are computer systems that draw inspiration from the biological neural networks that make up human brains. It is a type of artificial intelligence that attempts to imitate the way the human nervous system and brain work (Kriesel. 2005). The mathematician Walter Pitts and neurophysiologist Warren McCulloch first proposed the idea of ANNs in 1943, and since then, there have been several studies into its practical uses. However, a neural network is an algorithm used in cognitive activities like learning and improvement that is based on ideas from research into the nature of the brain. Since the propagation algorithm suggestion, the artificial neural network has developed and been used as an alternative for regression analysis (Akkol. 2015).

Due to its self-learning, self-organizing, and high-speed computing capabilities, ANN plays an important role in solving complicated nonlinear problems without assuming the relationships between variables (Patel and Jha. 2015). For these reasons, ANN is particularly well suited for resolving real-world construction management issues, which are challenging for traditional modeling and classical mathematics. Since the early 1990s, ANN has been employed in the field of construction management and can be used for prediction, optimization, classification, and decision-making (Chao and Skibniewski. 1995).

Many different input patterns and their corresponding output patterns can be used to teach it. The network develops the ability to offer solutions to new issues, even if they are insufficient, through the process known as training. There are typically two types of ANN tutorials: feed-forward and feedback ANN. The feedback network is self-feeding and well-suited for issue optimization, in contrast to the feed-forward network, which only sends data in the forward direction.

An example of a neural network having an input layer, a hidden layer, and an output layer connected is shown in Figure 4.

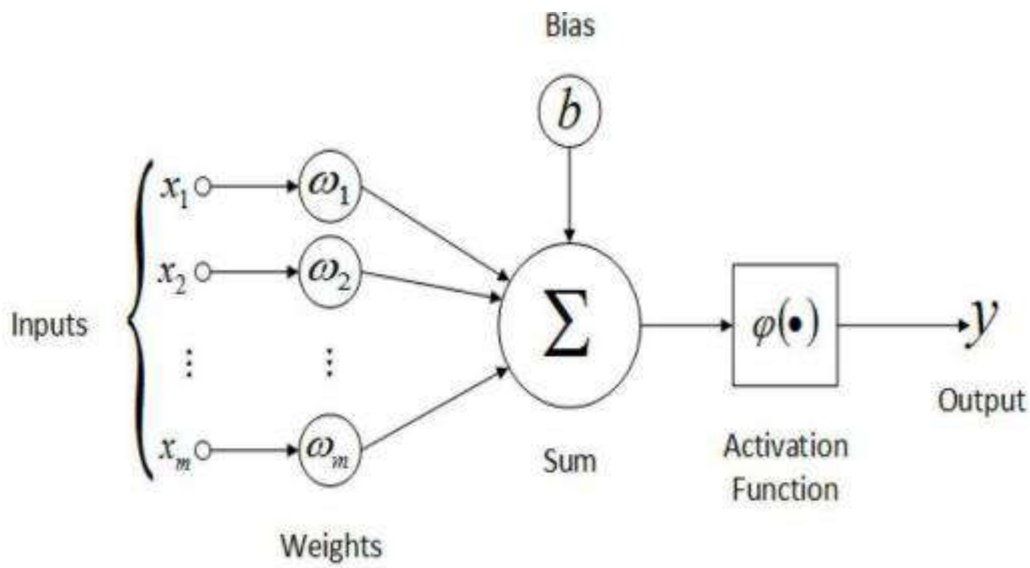


Figure 4: Basic structure of an ANN model. (Almusawi and Burhan. 2020).

The hidden neurons receive the weighted amount of input, which is then processed there using the activation function. The generated neurons then go through another transformation using the outputs of the hidden neurons as their inputs.

2.5.1 Previous Study on Artificial Neural Networks in the Construction Industry

Analysts typically use statistical techniques to extract patterns or information from data that has been collected. Yet, the use of statistical approaches falls well short of fully using the huge amounts of data in the construction business. Whether it be scheduling, estimating, safety analysis, or risk mitigation, new software is being fitted to every phase of construction (Pushkar, Senthilvel, and Varghese. 2018). Using machine learning enables the analysis of construction project data, which then offers useful insights and directs engineers and project managers during the decision-making process. Machine learning (ML) algorithms have been applied in a variety of project management areas, including time, cost, quality, safety, operations, and maintenance (Poh, Ubeynarayana, and Goh. 2018).

Four types of algorithms can be utilized in project management sectors for planning and estimation: classification, regression, association, and clustering (Kononenko and Kukar. 2007). Predictive models are used for both classification and regression, where classification produces categorical outputs and regression produces continuous variable outputs. Clustering is a segmentation technique in which comparable data are categorized, whereas the association is utilized to find connections between variables (Kononenko and Kukar. 2007).

Machine learning techniques have been adopted in numerous construction-related projects. Prediction is where artificial neural networks are most often used in construction management. The field of construction management has utilized artificial neural networks for the prediction of construction costs (Mohamed and Ahmed, 2013; Minh- Tu, Min-Yuan, and Yu-Wei, 2015); safe work behavior (Patel and Jha, 2015); safety (TaeKyung and Sang-Min, 2016); building valuation (YiCheng and Cheng, 2016); construction productivity (Li-Chung, Miroslaw and Skibniewsk, 1995; Jason and AbouRizk, 1997), labor productivity (Rifat, James and Rowings,1998).

In conclusion, it can be claimed that inadequate estimation causes unrealistic length, inappropriate budget consumption, and poor resource utilization and productivity rate to the total work, which negatively impacts the project's performance. One of the goals of this study is to construct a predictive optimization model for inventory control predictions that will be used in the future. This strategy might also be used during the planning stages of a ready-mixed concrete batching plant, giving the key players a standardized way to choose the economic order quantity and reorder point of raw materials as well as their optimal reservoir capacity for raw material storage.

2.6 Computer-Aided Simulation and Its Application in Construction Industry

2.6.1 Simulation and its technical term definitions.

The term "simulation" refers to a process that replicates how a real-world system functions as it changes through time. A simulation model is typically developed to accomplish this. A simulation model typically takes the shape of a collection of logical or mathematical relationships between the system's interesting elements that convey certain assumptions about how the system functions. The simulation process is running the model through time, typically on a computer, to produce representative samples of the performance measurements. When viewed in this light, simulation can be compared to a sampling experiment on a real system (Winston, 2003).

A simulation model could include intricate connections between various tasks that explicitly take into account resource utilization and unpredictability like variable weather patterns or unforeseen equipment breakdown. Both the input and output data for the simulation model are substantial. Advanced simulation technology is based on a sophisticated theory. A simulation is a representation of a real-world scenario that offers a framework for exploring and analyzing a specific scenario. Models include and reflect data that can be used to provide information that aids in decision-making when interpreted by predefined rules or conventions. These models' accuracy in simulating the real world varies greatly (Zayed and Halpin, 2001).

Computer simulation has been effectively used to analyze intricate systems in operations research and the manufacturing industry. A successful simulation model results from the inseparable cooperation between domain experts and simulation engineers (Chua & Li, 2002). Simulation models are increasingly being used to solve problems and to aid in decision-making. The accuracy of a model and its outcomes is a real concern for everyone involved, including the models' creators and users, decision-makers who use the data generated by the models, and the people who will be impacted by those decisions.

A simulation is a continuous imitation of how a system or process might work in the actual world. Whether carried out manually or digitally, simulation entails the creation of an artificial history of a system and its observation to derive conclusions about the operational features of the real system. A model can be used to research a wide range of "what if" questions concerning the real-world system once it has been created and validated. To determine their effect on system performance, potential system changes can be first simulated. Before such systems are built, simulation can be used to study them during the design phase (Banks et al. 2001). Therefore, simulation modeling can be used as a design tool to forecast the performance of new systems under various sets of conditions as well as an analysis tool for forecasting the impact of changes to existing systems.

Simphony simulation is the use of computer software (Simphony) to represent the dynamic responses of a construction system by the behavior of a Simphony model made to represent it. A simulation uses mathematical descriptions, graphical constructs, computer algorithms, or other means that are generally encapsulated in a simulation software model to represent the real system (AbouRizk et al. 2015). A construction system is any portion of the construction world (facility, environment, project, resources, etc.) that has been selected for studying the changes that take place within it in response to varying stimuli, documenting its dynamic behavior, or optimizing its performance. Generally, a simulation model is defined as a composition of objects (often associated with graphical notations) that represent an abstraction of the construction system (AbouRizk et al. 2015). The abstraction often takes the form of ideas that define the system's constituent parts and behaviors that the modeler deems important for the model.

2.6.2 Simulation in Construction Operation

The science of creating and testing computer-based representations of construction systems to comprehend their underlying behavior is known as construction simulation. To forecast how productive construction operations will be and how well project schedules will perform, simulation modeling is crucial (Lee et al. 2010). Regardless of their complexity or scale, computer simulation techniques are very effective in this field at providing the tools needed to design and analyze construction processes (Hajjar & AbouRizk, 1999). Because it makes it possible to observe technological and logical dependencies, and resource availability limits, and analyze the effects of potential variations on the overall project performance, computer simulation ensures more realistic structuring and planning of construction operations.

Construction operations can be modeled, analyzed, and optimized using computer simulation. It is a tried-and-true method, and numerous studies have been conducted to show that it can be used to analyze a variety of construction operations, including aggregate production, earthmoving, mining, tunneling, and the production of precast concrete (Hajjar & AbouRizk, 2000). Decision-makers can analyze various construction processes and alternatives with the use of construction simulation. Construction industry professionals and analysts can experiment with various construction technologies and calculate the potential effects and impacts on scheduling and costs through the simulation of construction activities.

One of the effective tools for assisting in construction management decision-making is simulation. The development of better solutions and the optimization of the resources used can both benefit from accurate modeling of a construction process. Simulation methods are thought to be used very little in the building business. Weak simulation application in construction management is mostly caused by the complexity of simulation approaches and the lack of in-depth simulation understanding among industry personnel (AbouRizk & Mohmed, 2000).

Simulation is applied in the operations of construction projects. The major justifications for utilizing the simulation for construction operations are outlined in the list below (Ruwanpura et al. 2000).

1. ***Project Planning***: Simulation can model a hypothetical situation using a computer. This enables the planners to use simulation to plan the sequence of work activities, declare the method of operation, select the suitable resources for the given project, and analyze the production of the system before commencing actual construction.
2. ***Identifying bottlenecks in construction operations***: Some of the problems that may happen in atypical construction projects could be detected using the results of the simulation model. Identification of these problems helps planners and engineers to decide on corrective measures before actual construction commences.
3. ***Examining productivity improvements and optimizing resource utilization***: The typical outputs of a simulation model for construction are productivity, productivity advance rate, and resource utilization. Using a simulation model, planners and engineers can observe productivity and resource utilization levels and conduct additional testing to improve the efficiency of the system using the available resources.
4. ***Offering a quick comparison of alternative construction scenarios***: This is one of the main advantages of using simulation for any construction operation. Simulation allows planners to not only predict the actual results but to compare the results using several scenarios. Simulation offers a very quick comparison for alternate scenarios and allows the planners to make informed decisions before they embark on the project.

Simulation can be useful in the building industry in numerous ways. For example, during design: can be used to analyze Risk, Value, Constructability reviews or scenario-based planning, Construction plan development, Budget development, and Estimating. Planning and control, ongoing improvement, claims, and conflict settlement, etc. during and after construction (AbouRizk et al. 2015).

2.6.3 Simulation Software Used in Construction Operation.

Usually, discrete-event process interaction modeling has been the predominant way of simulating building processes. This strategy is used by several simulators to represent a construction operation utilizing precise modeling. It is an intrinsically difficult task for the simulator to explain the industrial process in question in a specific simulation language. Much progress has been made to make the use of discrete-event process interaction simulation in building easier (AbouRizk and Hague, 2009).

Table 3. Some of the simulation software's developed to stimulate the construction operation process

Author's Name & Publication Year	Simulation Software	Purpose
Hajjar & Abou Rizk (1997)	AP2-Earth	for the analysis of large earthmoving projects
Hajjar & Abou Rizk (1998)	CRUISER	for modeling aggregate production plans,
Hajjar & Abou Rizk (1999)	SIMPHONY	for DES system
Shi (1999)	ABC (Activity-Based Construction)	for modeling general construction processes
Chua & Li (2002)	RISim	for simulation modeling construction operation
Lu et al. (2003)	HKCONSIM	for modeling ready mix concrete production operation
Abou Rizk & Hague (2009)	COSYE	for capturing all features, resources, and processes required to design, build and maintain a facility
Siadat & Ruwanpura (2013)	EarthSim	for modeling earthmoving projects

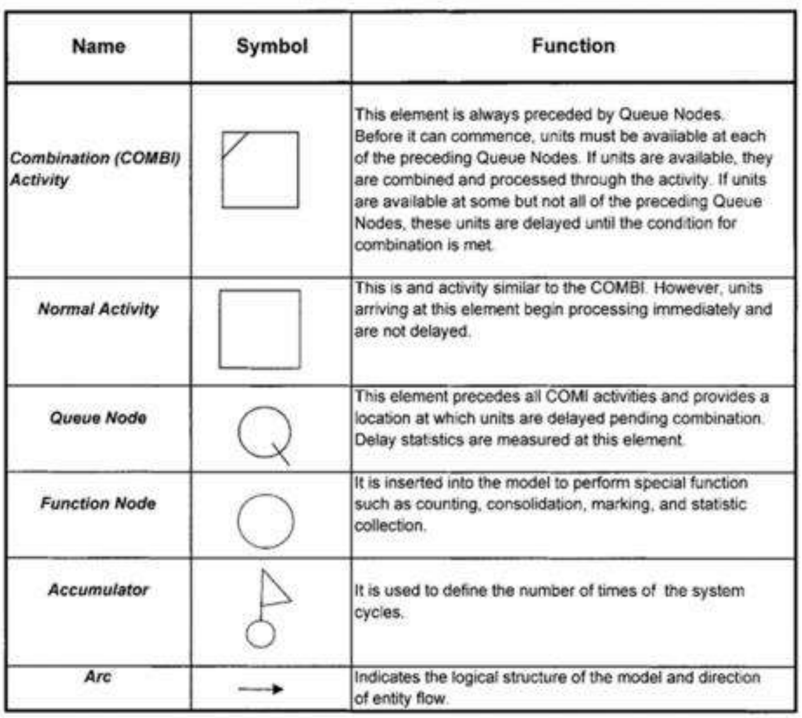
DES-based systems at the operation and project levels are independently used to improve operational productivity and scheduling performance. These systems are well accepted in a wide range of applications in practice (Lee et al. 2010). UM-CYCLONE (Ioannou, 1990), Micro CYCLONE (Halpin and Riggs, 1992), CIPROS (Tommelein et al. 1994), STROBOSCOPE (Martinez, 1996), ABC (Shi, 1999), and SIMPHONEY (Hajjar & AbouRizk, 1999) are among the several custom developed simulation packages specially designed for construction projects based on CYCLic Operation NEtwork developed by Halpin (1977) (Zahran & Nassar, 2013; Jabri, 2014).

The literature mentioned above describes a variety of simulation software programs and planning optimization methodologies that have been created and used in construction operations. The most well-known simulation is, however, listed and explained as follows.

2.6.3.1 CYCLONE/Micro-CYCLONE/UM-CYCLONE

Halpin (1977), created CYCLONE (CYCLic Operations Network). Using the modeling method CYCLONE, discrete systems that deal with stochastic or deterministic variables can be graphically represented and simulated. Construction professionals with little simulation experience can use CYCLONE to generate simple simulation model processing (Purdue University, 2020). One of the earliest simulation languages created for use in the construction industry is CYCLONE, which primarily concentrates on simulating the construction process rather than the system. In CYCLONE, the construction process is abstracted and modeled as operations and processes made up of queues and tasks. (AbouRizk et al. 2016).

CYCLONE / Micro CYCLONE Simulation model systems can be applied to the modeling of concrete batch plant operation to study different combinations of resources. Micro-CYCLONE modeling and programming systems can be used to simulate this process. The CYCLONE elements used for construction modeling are shown in Figure 5, (Halpin, 1992). Micro-CYCLONE is a simple and powerful tool for construction process planning, as demonstrated by many researchers (Zayed and Halpin, 2001).



Name	Symbol	Function
Combination (COMBI) Activity		This element is always preceded by Queue Nodes. Before it can commence, units must be available at each of the preceding Queue Nodes. If units are available, they are combined and processed through the activity. If units are available at some but not all of the preceding Queue Nodes, these units are delayed until the condition for combination is met.
Normal Activity		This is and activity similar to the COMBI. However, units arriving at this element begin processing immediately and are not delayed.
Queue Node		This element precedes all COMI activities and provides a location at which units are delayed pending combination. Delay statistics are measured at this element.
Function Node		It is inserted into the model to perform special function such as counting, consolidation, marking, and statistic collection.
Accumulator		It is used to define the number of times of the system cycles.
Arc		Indicates the logical structure of the model and direction of entity flow.

Figure 5. Basic CYCLONE Modeling Elements. Developed by (Halpin 1992). Adapted by (Zayed and Halpin 2001).

UM-CYCLONE is an integrated modeling environment created by a group of programs that form a discrete event simulation system. A network of connected nodes, including Activities, Queues, and Consolidation Nodes, makes up a UM-CYCLONE simulation model (Ioannou, 1990).

2.6.3.2 STROBOSCOPE

STROBOSCOPE (STate and ResOurce Based Simulation of COnstruction ProcEsses) (Martinez et al. 1994; Martinez & Ioannou, 1994) is a programming language specially designed to model construction operations. Stroboscope models are built on a network of interconnected modeling elements and a set of programming instructions that give each element a distinct behavior and regulate the simulation (Marzouk & Moselhi, 2003).

Mohamed & AbouRizk (2006) state that Stroboscope gives the user the capacity to dynamically access the simulation's state as well as the characteristics of the resources used in the operation. Programming statements used to define the attributes of stroboscopic modeling elements also specify how they should behave during simulations (Jabri, 2014; Martinez et al. 1994).

Stroboscope can be used to create simulation models for many construction processes, including the operation of the quarry (Martinez & Ioannou, 1995), the earthmoving operation of dam building, and the Airplane Service center (Ioannou & Martinez, 1996).

Stroboscope's functionality can be increased by adding add-ons created using the add-on interface in compiled languages like C++, PASCAL, and FORTRAN (Martinez, 1996). For instance, using the CPM Add-on program for Stroboscope, Martinez & Ioannou (1997) created a simulation model of probabilistic CPM scheduling for food-outlet construction operations.

2.6.3.3 SIMPHONY

Although improvements to CYCLONE now offer explicit resource representations, more recent modeling systems like Simphony or STROBOSCOPE have many features to offer greater modeling flexibility, such as the capability for users to write their programming code to manipulate the model and its components for more accurate modeling (AbouRizk, 2010).

Simphony is a computer system that runs on Microsoft Windows and was created to offer a standardized, reliable, and intelligent environment for both the creation and use of building SPS (Special Purpose Simulation) tools. Simphony enables tool designers to quickly and easily construct extremely versatile simulation tools that support graphical, hierarchical, modular, and integrated modeling (Hajjar and AbouRizk, 1999).

2.6.4 Application of Simulation in planning concrete delivery process.

To improve processes, reduce waste, and produce higher-quality goods, the construction industry has become more and more reliant on certain techniques. In this situation, internal assessments of the procedures used at the construction site are crucial. The supply chain's analysis and simulation can help the building industry's techniques be improved.

Markus et al. (2011), especially in large-scale or inner-city projects, logistic operations frequently play a significant part in building project planning. The analysis of the influences of logistic aspects on the construction processes in early planning phases allows the discovery of limitations in terms of the project schedule. Early planning uses of logistic simulation often include

- Generation of time schedules based on material flow specifications, milestones and framework dates, and available resources.
- Evaluation of different logistic concepts and identification of possible bottlenecks. This compromises alternative storing and transportation strategies.
- Analysis of reliability and strength of time schedules by considering possible disturbances and uncertainties regarding the available project data.

Different researchers have been used different kinds of simulation technic to solve the problem related to concrete works, the research work listed as the following

1. Smith (1998) has developed a concrete supply model using coded Visual Basic for Excel and has concluded that one of the factors to maximize performance in the concreting method would be to reduce the arrival rate of concrete mixer trucks.
2. Scheduling the Truck Mixer Arrival for a Ready Mixed Concrete Pour via Simulation with @Risk software, by Wang et al. (2001), the objective of this study is to develop a simulation model, taking into account the popularity and benefits of spreadsheet and @Risk software in the construction industry, to find the best arrival pattern for truck mixers that will maximize the productivity of RMC placing on-site, particularly the utilization of RMC placing resources.

3. Concrete batch plant production by Zayed and Halpin (2001), state in the objective of their research "The results of the study provide a means of predicting systems production and defining optimum supply areas around a concrete batch plant. The optimum areas support efficient resource allocation with minimum duration and cost for different distances".

4. Concrete Mix Transportation Modeling by Kozniewski and Orlowski (2003). Used a simulation to study "transport mix operation and the study provides predicting of system production and defining the optimum number of truck mixers and their kinds".

5. Integrating fmGA (fast-messy genetic algorithms) and CYCLONE to optimize the schedule of dispatching RMC trucks by Feng and Wu (2006). Develop, "the fast-messy genetic algorithms (fmGA) and the CYCLONE simulation technique" to optimize the dispatching process of RMC.

6. A Simulation-Based Decision Tool for Transportation of Ready Mixed Concrete by Marzouk and Younes (2013). Develop "A decision support tool for planning one plant – one - site operation using computer simulation".

7. Dispatching concrete trucks using the simulation method by Biruk (2015). Biruk used a simulation model to "access alternative strategies for truck allocation and production planning in the stochastic environment".

8. Azambuja and Chen (2014) conducted a simulation to assess supply chain risks to identify vulnerabilities and measure the impact of ruptures in the machined concrete supply chain. For this, they implemented a tool for fault diagnosis, effects, and critical analysis (FMECA).

9. Sileshi (2018) develop "a simulation model for planning of ready-mix concrete (RMC) site delivery using Simphony- CYCLONE". The main objective of this study is to identify and develop an effective method of planning RMC site delivery in Addis Ababa city from one plant to one site.

2.7 Construction Simulation in Ethiopia

Construction simulations and models in Ethiopia are still in their initial stages at the university research level and have not yet begun to be used in actual construction projects. Some researches related to modeling and simulation of the construction industry in Ethiopian are: (Getachew, 2016) conducted the role of building information modeling (BIM) in improving the building design process, (Matheas, 2009) and (Alemayehu, 2014) developed a Multiple Linear Regression model (MLR) to analyze the design, and cost-effectiveness of pre-cast beam slab system and to estimate the cost of road construction projects respectively using Multiple Linear Regression model (MLR), (Kassahun, 2018) and (Taye, 2019) developed Monte Carlo Simulation model for cashflow forecasting for building construction projects and cost overrun in construction projects respectively.

Moreover, there is also some other simulation modeling research related such as a factor model to predict the construction labor productivity in building projects using the Multiple Linear Regression model (MLR) (Arnaud, 2019), a simulation model for optimization of tower crane location in high-rise building projects using Particle Swarm Optimization (PSO) (Ketema, 2019), a simulation model for the Analysis of Earthmoving operations using Discrete Event Simulation (Yemane, 2020), and simulation model for planning of ready-mix concrete (RMC) site delivery using Simphony-CYCLONE (Sileshi, 2018).

2.7.1 Ready Mixed Concrete Site Delivery Simulation: Previous Research

The construction industry in Ethiopia is boosting a high growth rate due to the need for infrastructure and other business sectors in the country. It contributes about 24.82% of the Country's GDP as reported in 2019. As the concrete technology stands now, ready-mix concrete is leading the infrastructure development in Ethiopia's capital, Addis Ababa. Considering the high engagement of the City Government in vertical settlement development programs of condominiums and apartments, and other financial sectors and banks are building high-rise buildings, concrete is a major input to bring the effort to fruition. For this, RMC is the perfect choice to tackle the intricate situation of inner-city development (Kassahun 2017).

One of the most often used building materials in the construction sector is ready-mix concrete. RMC is often made in a concrete batch plant, where materials are measured and mixed automatically to meet construction site requirements. Due to its many advantages over conventionally prepared concrete, such as homogeneity and speed of production, RMC is frequently utilized for all sorts of construction. RMC commonly needs to be poured within a short time, after being produced by the RMC batch plant, which restricts the service area of delivery. As a result, the RMC sector is worried about production and truck-delivering planning. Even though skilled staff can handle delivering scheduling manually, there is a chance that construction site interruptions will result. So, preparing an efficient schedule for delivering RMC trucks is very important, which will optimize the waiting time of RMC trucks at the construction sites and also at the batch plant.

A study on Ready-mixed Concrete site delivery simulation for Ethiopian construction industry began a few years back (4 years) because it was introduced to the Ethiopian construction industry very recently and has a short year of records or history, so far there is only one study by Sileshi (2018) in titled with "planning ready mixed concrete site delivery in Addis Ababa". The study used Simphony CYCLONE software for developing different models from one plant – to – one site RMC delivery.

The study emphasizes on identifying and developing an effective method of planning ready mixed concrete site delivery in Addis Ababa city. Computer-aided simulation software called Simphony CYCLONE is used to study the characteristics of one plant-to-one site concrete delivery operation.

Table 4. Summary table for the finding and limitations of the study conducted by (Sileshi, 2018).

Developed models based on	Findings	Limitations
1. Concrete delivery time A. Day time B. Night time	Daytime delivery (22.28 m^3/hr.) is 35% more productive to cast horizontal structures	It is only considered one plant-to-one site concrete delivery
2. Poured structure element B. Vertical structure C. Horizontal structure	Night-time delivery (21.01 m^3/hr.) is 49% more recommended to cast vertical structures	The study only limited to delivery of concrete to sites

Table 4. Illustrates the developed models, findings, and limitations of the study conducted by (Sileshi, 2018). The study developed different models based on the concrete delivery time (Day time and Night time) and poured structured elements (Vertical structure and Horizontal structure)

Using the above models, the study identifies the most critical or highly valuable resource and the factors that mostly affects concrete site delivery performance and reached a conclusion that, day-time delivery is more productive to cast horizontal structure and night-time delivery is recommended to cast vertical structure with an optimized number of station pump.

As a result, it was discovered that the production rates for daytime deliveries were 22.28 m^3/hour and nighttime deliveries were 21.01 m^3/hour, respectively. According to the research on the difficulties of casting structures, horizontal structures are 35% more productive during the day-time and 49% more so at night-time than vertical structures.

The limitation of the study is:

- It is only considered one plant – to – one site concrete delivery operation
- It is only limited to RMC site delivery operation

2.8 Identified Research Gap

A research gap is simply an open question or an unsolved issue in a discipline that shows a lack of existing research in that area. A research gap can also exist when there is a good number of existing research, but it is challenging to make conclusive conclusions since the results of the studies pull in various ways.

The Construction industry in Ethiopia has been implementing many projects to meet society's needs in the future. RMC is one of the aspects of the construction industry which helps to get the required quality and speed of construction. This has amplified the demand for RMC, the RMC batching plants are working on supplying RMC to satisfy the huge demand for concrete works on construction sites. For any business to satisfy the demands and desires of its clients, materials or inventory are crucial prerequisites. The crucial component for the success of construction projects nowadays is the management of this inventory and the delivery of the resources as needed. Its proper storage capacity, ordering and handling, delivery, and full and accurate information regarding on-site stock all have an impact on inventory control. Planning based on having an efficient inventory management process can result in a better or worse inventory control system.

However, the overall inventory practice was ineffective because of a demanding, judgmental system, large purchases made with limited storage, and poor supervision. Product delivery and understanding of using inventory management techniques are the primary contributing elements. As a result, a scientific approach to good inventory control procedures and simulation for the delivery of produced goods is required, as using this model will help the association determine the ideal number of items to order within a given timeframe and when to place new requests for each item, in addition to providing the productivity rate and resource utilization for the delivery process.

(Sileshi, 2018) have identified that RMC delivery operations will optimize the production rate and minimize the challenges. However, in addition to the delivery of RMC to sites appropriate supply chain management, like inventory management which is interlinked to the delivery of RMC is essential to solve a problem related to concrete batching plants.

Moreover, there is limited research that is done on integrating or interlinking material inventory control with the delivery of RMC. Therefore, this study tries to fill the gap and addressed the issue.

III. CHAPTER THREE - RESEARCH METHODOLOGY

The Research Methodology

Research methodology identifies the research basis, design, and analysis to methodically answer the research problem. In light of this, the next chapter discusses the research's methodology.

3.1 Introduction

3.1.1 Research Definition

Research refers to a careful, well-defined, objective, and systematic approach to knowledge search or the formulation of a theory motivated by inquisitiveness for that which is unknown and helpful in a particular area to make a unique contribution to broadening the base of existing knowledge. Kumar (1999) states, "Research is defined as collecting, analyzing and interpreting information to provide a solution for a question or problem." With this foundation, research design and methodology serve as a means of tying all research procedures together and directing the researcher toward the study's objective.

3.1.2 Type of Research

Even though different authors have authored different types of research, the concepts are essentially the same. Hence, according to Deb and Balas (2019), the different types of research are;

I. Descriptive versus Analytical*:* Descriptive research includes comparative and correlational methods, and fact-finding inquiries, to effectively describe the present state of the art. The researcher only reports what is and has no influence over the variables. Attempts to identify reasons are also part of descriptive research even when the variables cannot be controlled. On the other hand, analytical research makes use of already-known facts for analysis and critical review. Some research projects might be both analytical and descriptive.

II. Applied versus Fundamental*:* Research can either be applied research or fundamental (basic or pure) research. While fundamental research is focused on making generalizations and developing a theory, applied research aims to solve an immediate problem facing the organization.

III. Quantitative versus Qualitative: Quantitative research uses statistical observations of a sufficiently large number of representative cases to draw any conclusions, while qualitative researchers rely on a few non-representative cases or verbal narratives in behavioral studies.

This research has adopted the above classification and is thus descriptive, correlational, applied, and quantitative research. It is *descriptive* as it collected information without changing the environment (i.e., nothing is manipulated) and tries to describe the integrity and relationship, by systematically viewing the problem and undoubtedly seeks the *correlation* of EOQ based ANN Prediction model with the Delivering model for the overall optimization of the batching plant. It is *applied* as it tries to analyze existing information to arrive at the objectives of research outcomes or reach decisions. It is also *quantitative* as it tries to quantify the relationships and develop parameters for future use. The outcome of this research is applied in the respective study areas after the developed model is validated using statistical analysis.

3.1.3 Research Process

The research process involves several steps that make it easy to complete the research successfully. The research process is therefore concerned with collecting data and processing it into information. People can use the information thus created to add to their knowledge, perhaps even developing wisdom.

According to Singh. (2021), a Research Process is a process of multiple scientific steps in conducting the research work. Each step is connected to the preceding phases. The process starts with the research problem at first. It then proceeds consecutively through the subsequent phases.

Towards achieving the research goal, a flow chart that shows the structure of the whole process is designed before starting the research work. The Research Process flow chart presented in Figure 6 shows how the research work proceeds in a structured way to make the work effective.

This research uses the EOQ inventory model, Machine learning tools (Weka 3.8.6), and Simulation software (Simphony. NET 4.6) to develop the models, and their process is discussed under the method of data analysis section.

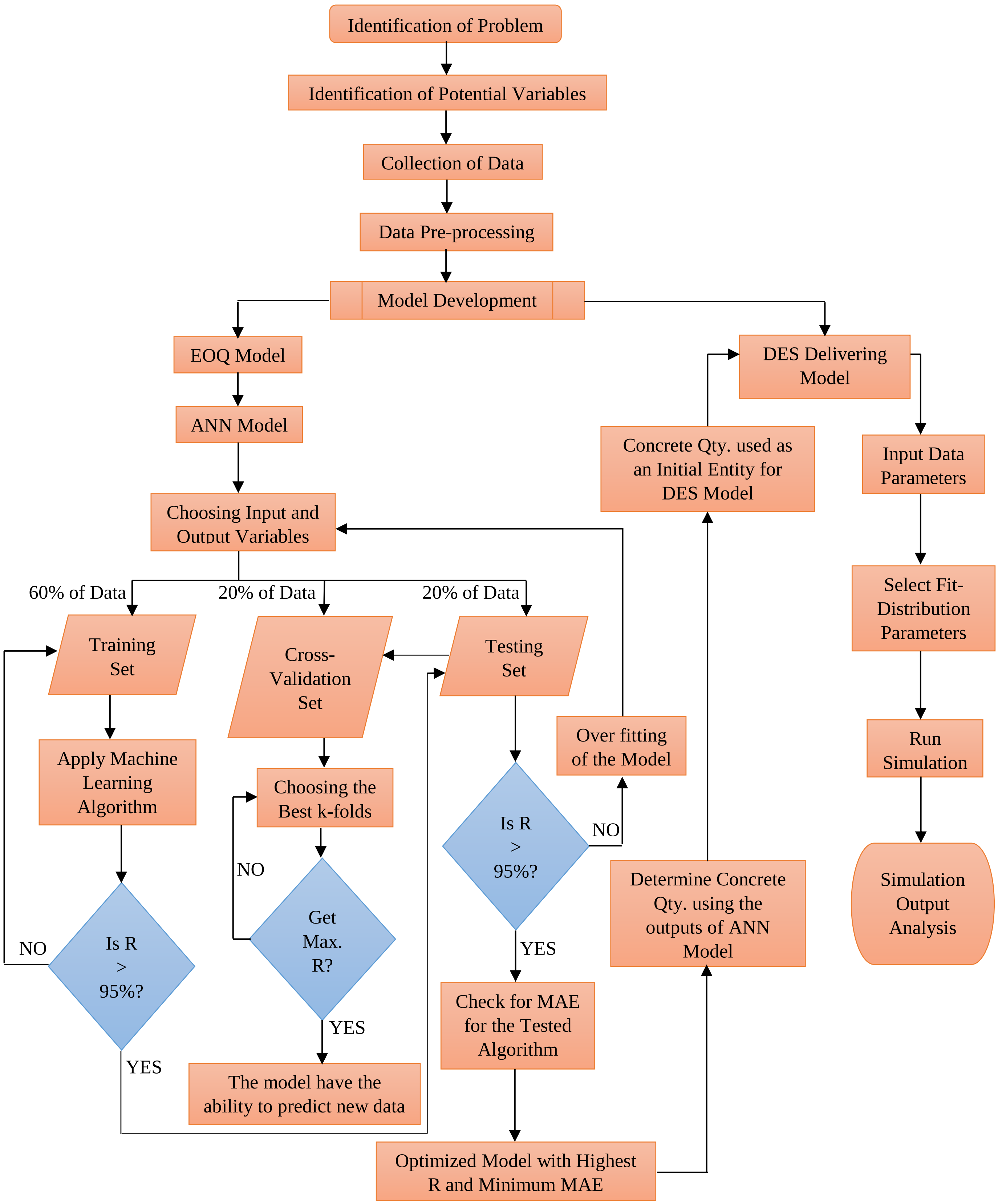


Figure 6. Research Process flow chart for this research

The study's research process was as follows, as indicated in Figure 6: Potential variables for determining raw material inventory control and delivery were found through a review of earlier studies and literature. The data needed for the study were collected through observation and document screening, and data outliers were removed from datasets before the construction of the model to reduce their impact on the generated model's ability for prediction. Later, EOQ, ANN, and DES models were developed using statistical, machine learning, and simulation tools; the methods of data analysis will discuss in Chapter 4 Research Design.

The preparation of the research project's design is the second-most crucial issue after determining the research problem. That is officially referred to as the research design. Research design is the overall strategy for acquiring the answers to the questions posed as well as the subsequent management of some of the challenges faced during the research process. It is a strategy for getting from "here" to "there," where "here" may be interpreted as the initial set of questions that need to be resolved and "there" as the conclusions (solutions) to those findings. There are several significant phases between "here" and "there," including the collection, interpretation, and analysis of pertinent data. According to (Kothari. 2004), the research design decision shall be in respect of the following questions:

Table 5. Research questions and answers.

Question	Answer
a) What is the study about?	Provide a model for raw material inventory control and delivery of RMC to sites
b) Why is the study being made?	For academic achievement and to provide a useful tool for RMC batching plant
c) Where will the study be carried out?	On a selected batching plant in Addis Ababa
d) What type of data is required?	Qualitative data are required for this study
e) Where can the required data be found?	From the selected batching plant and sample projects
f) What periods will the study include?	The study period includes the full year of 2014 E.C.
g) What techniques of data collection will be used?	Observation and document screening (financial reports and cost break-down)
h) How will the data be analyzed?	By using an Excel-based spreadsheet, WEKA 3.8.6, and Simphony. NET 4.6 software.

Thus, based on the above ideas, the research has been designed in the following sections.

3.1.4 Description of sample projects

To develop a better understanding of the challenges associated with ready mixed concrete batching plant inventory and delivering optimization and to solve the problems, it is important to identify the implementation area of the ready mixed concrete batching plant, construction project, types of construction, density, and complexity of construction. Accordingly. Several Ready mixed concrete batching plants exist in Addis Ababa. This research has sampled one of the active and high-capacity batching plants in the city.

To achieve the objectives of this research, it is also important to select a sample project (case study) from the selected ready-mixed concrete batching plant for delivering concrete to sites. The selected sampled projects are road projects under construction. Namely, Bole Homes – Gumruk Road Project and Sansusi – Tatek Kela Road Upgrading Project.

Here below the descriptions of the selected ready-mixed concrete batching plants and selected sample projects for delivering concrete to sites are summarized. Figure 7 and Figure 8, demonstrate the location of both sites (the construction and the plant site) and the optional access road to deliver concrete from the plant site to the construction sites with their distance.

- **RMC Batching Plant**

  Location: - Addis Ababa

  Capacity: - Two mixers with fully computerized 120 cubic meters per hour

Table 6. Selected sample projects for delivering concrete to sites.

	Project 1	Project 2
Project Name	Bole Homes – Gumruk Road Project	Sansusi – Tatek Kela Road Upgrading Project
Length	0+000 Km – 4+900 Km	0+000 Km – 14+000 Km
Route	Route C	Route A and Route B
Avg. distance from batching plant	Route C (5.7 K.M)	Route A (23 K.M) and Route B (27 K.M)
Location	Bole Sub-City	Western Addis Ababa
Client	Addis Ababa City Road Authority (AACRA)	Ethiopian Road Authority
Consultant	United Consultant	Hitcon Consultant and Fortress Consultant
Contractor	Aser Construction Plc	Aser Construction Plc

Figure 7. Sample project location, concrete batching plant, and delivery site (Site 1).

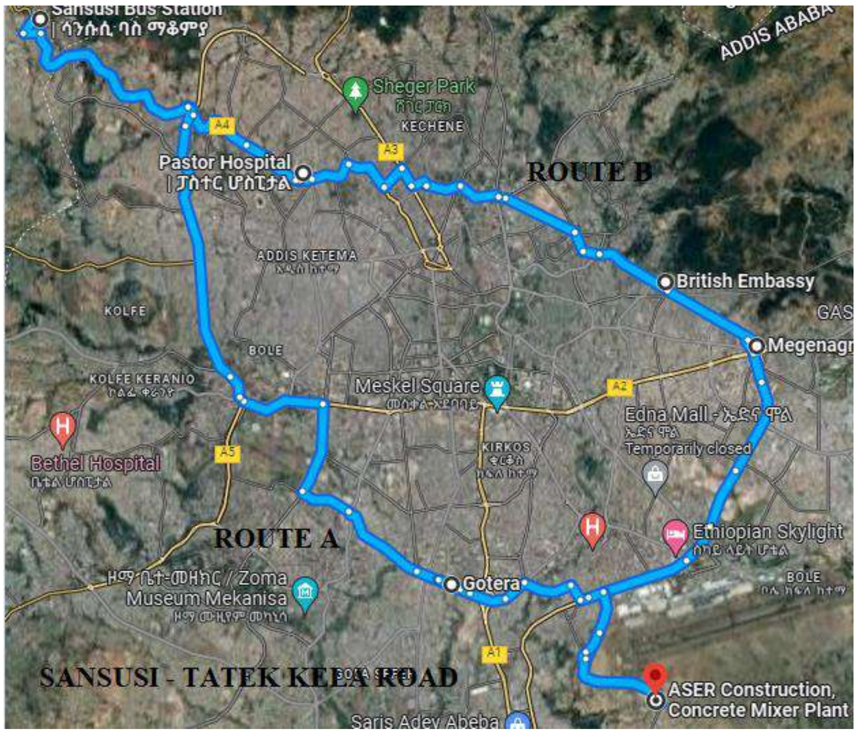


Figure 8. Sample project location, concrete batching plant, and delivery site (Site 2).

3.1.5 Selection of Research Method

Research methods are the tactics, procedures, or techniques used in data gathering or evidence analysis to find new information or improve understanding of a topic. It takes careful planning and execution to do research successfully. Even if some many factors and features contribute to a good research completion, choosing the right research method is one of the hardest and most confusing decisions. When research methods are chosen properly, it is possible to get the necessary data and achieve the study's objectives.

The two main categories of research methods:

I. ***Qualitative Research***: - Utilizes data that cannot be quantified numerically.

II. ***Quantitative Research***: - Utilizes numeric and statistical data.

For this research quantitative research approach has been selected, this is mainly because the research is focused on data analysis and utilizes quantified numerical data for the analysis of the developed model

The most frequently used methods include:

I. ***Observational Research***: - counting the number of times a specific phenomenon occurs.

II. ***Case Study Research***: - is used to generate an in-depth, multi-faceted understanding of a complex issue in its real-life context.

III. ***Survey or Questionnaires Research***: - is the process of collecting, analyzing, and interpreting data from many individuals.

IV. ***Document Screening Research***: - sourcing numerical data from financial reports.

V. ***Experimental Research***: - based on conducting tests.

This research has selected three different approaches from the above-listed most frequently used research methods. For delivering model analysis 182 observational data are collected for each of the seven different activities (Loading, Travelling, Positioning, Dumping, Washing at the site, Returning, and Washing at the plant) using two sampled projects (Case Study), again for the inventory and artificial neural network model a full one-year observational data and document screening data are used.

However, the case study research approach is questioned for its lack of sufficient information required for scientific generalization and openness to subjective bias, this research fills the gap for having lack of sufficient information by taking a case study sample projects which account for **50.89%** of the total available data, additionally, for inventory and artificial neural network model, all the necessary data are collected throughout the year daily. This makes the collected research data unbiased and representative.

3.1.6 Data Source and Collection.

According to Kumar (1999), data sources can be divided into two Primary and Secondary. Primary data is collected from Primary sources like Observation, Interviewing, and Questionnaires, and Secondary data is collected from Secondary sources like documents: Government publications, earlier research, financial reports, and personal records. The data sources used in this research are observation and financial reports. Meanwhile, the financial report data have not been used for any other related research purpose, according to Kumar (1999) it is regarded as Primary Data for this research.

The source of data for this study is a selected concrete batching plant and Addis Ababa City Administration Construction Bureau (AACACB). According to Kumar (1999), the following ethical concerns shall be looked into by any researcher in data collection: avoiding bias, provision or deprivation of treatment, using appropriate research methodology, correct reporting, and using information. This research has tried to consider the above ethical issues in the stage of data collection.

3.2 Sampling Method

Sampling is the process of choosing a portion of an aggregate or totality from which a conclusion or judgment aggregate or totality is drawn. In other words, it is the method of learning details about a whole population by looking at a small portion of them. The typical method in the majority of research projects and surveys is to generalize about or draw conclusions about the characteristics of the population from which the samples are gathered (Kothari, 2004). Concrete batching plants located in Addis Ababa City are the study's targeted population. According to information from the Addis Ababa City Trade Bureau and the Construction Works Regulatory Authority, there are 38 concrete batching plants in the city as of 2021 and 2022.

To choose a representative sample for this study, purposive sampling was used.

The main reasons to justifying why it is important to select a concrete batching plant and the selected sample projects (case study) for this research are:

I. It is one of the batching plants which started operation in the year 2015 G.C by installing two modern and fully computerized 120 cubic meters per hour Concrete Batching Plants. This makes the company that stayed in the business for a long with high concrete production capacity, and their experience in the business helps us to get unbiased and consistent data for the models.

II. The company has a constant supplier of raw materials of sand and aggregate. Additionally, they have their crusher plants located in the city, which makes the batching plant have continuous production of concrete, and this helps to obtain enough data needed by the research during the given period.

III. The concrete batching plant and both sampled projects are owned and executed by one construction company, which allows for the data collection process to be simple and realistic.

IV. The selected projects are demanded a continuous supply of concrete, (Bole Homes – Gumruk road project and Sansusi – Tatek kela upgrading road projects demanded **29.34%** and **21.55%** of the company’s yearly concrete production respectively.) which makes **50.89%** of concrete demanded for both projects from the overall yearly concrete production of the company. This helps to obtain representative enough data needed for the simulation model.

V. Best option for developing a simulation model due to

  - ✓ The projects are located in the city and outskirts of the city. This location difference helps to have different data on delivery due to site location distance from batching plant, access road, and traffic conditions.
  - ✓ The projects have different structures to be cast, this again helps to have different data in the model, which makes to create an overall representing simulation model.

VI. The experience learned from this modeling approach and sample projects can be used for similar ready-mixed concrete batching plants and projects. There are many ready-mixed concrete batching plants in Addis Ababa, and the developed inventory, artificial neural network, and simulation model will also be useful for those batching plants.

3.3 Methods of Data Analysis

An appropriate method of data analysis is very necessary to be able to accurately process the data that is collected. The analysis of this research has been carried out by using an excel based spreadsheet, WEKA 3.8.6 as a data mining and machine learning tool for the prediction of EOQ-based artificial neural networks and Simphony. NET 4.6 for analyzing ready mixed concrete delivery to sites.

IV. CHAPTER FOUR - RESEARCH ANALYSIS AND DISCUSSION

4.1 Proposed Conceptual Model of the Research

In this study, a dataset based on observation and document screening (financial reports) of the selected concrete batching plant was used in an inventory control model called Economic Order Quantity (EOQ), and optimal order quantity, as well as raw material reordering point of the batching plant, was calculated. Then develop the EOQ-based Artificial Neural Network (ANN) model of the raw materials inventory control for the prediction of the optimal order quantity and reordering point of the raw material. Using the ANN predictions of optimal order quantity, the optimal number and size of the raw material reservoirs of batching plants can be estimated with a simple mathematical calculation which was the most important goal of this research. The optimal estimation of the material reservoirs could result in the best use of the land, which reduces the plant's initial investment needs. Another goal of this study was to integrate EOQ-based ANN prediction with the DES delivering of concrete to sites model, for this integration, ANN predictions of optimal order quantity of concrete are used as an initial entity (input) for the DES delivering of concrete to sites model. This helps us to get optimal productivity and utilization of resources for the batching plant. Figure 9 displays the proposed conceptual model of what was previously explained.

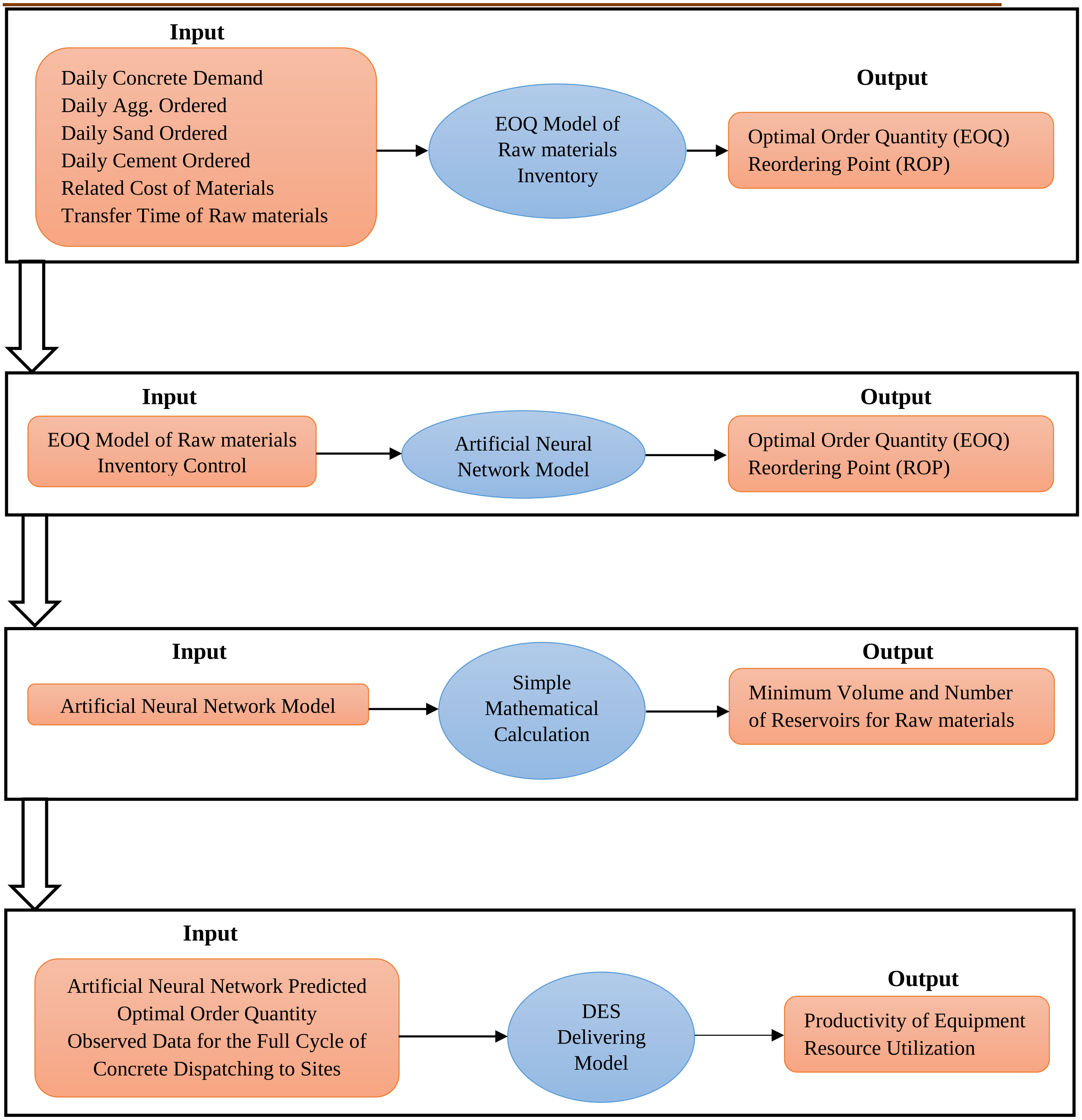


Figure 9. Summary of the proposed framework.

4.2 Analysis of The EOQ Model for raw materials

The first analysis of this research is the EOQ model, which is the most common model of inventory control which determines the optimal order quantity of each material considering with which total inventory costs (holding and ordering) can be minimized.

It is stated as follows:

$$Q^* = \sqrt{\frac{2aK}{h}} \quad \text{(Eqn. 1)}$$

Where Q^* is the optimal order quantity, a is the demand per unit of time, K is the setup cost for ordering one batch, and, h is the holding cost per unit of time held in inventory.

And, the corresponding cycle time is expressed as follows:

$$T = t^* = \frac{Q^*}{a} \quad \text{(Eqn. 2)}$$

Where T is the cycle time or length, Q^* is the optimal order quantity, and a is the demand per unit of time.

Whereas for reordering point:

$$\mathrm{ROP} = \mathrm{LT} \times \mathrm{D}, \text{ where L} < \text{T} \quad \text{(Eqn. 3)}$$

$$\mathrm{ROP} = \mathrm{LT} \times \mathrm{D} - \mathrm{n} \times Q^*, \text{ where L} > \text{T} \quad \text{(Eqn. 4)}$$

Where ROP is the reordering point the of material, LT is the lead time demand, D is the demand per unit of time, L is the length of delivery of materials, T is the cycle length, n is the number of orders on the stock cycle, and, $Q^*$is the optimal order quantity.

This research has used the above equation with the help of an Excel spreadsheet formula for the formulation of the EOQ model of raw material inventory control and reordering point of raw materials.

4.2.1 Data Collection

The data was collected from a selected concrete batching plant and Addis Ababa City Administration Construction Bureau (AACACB). The data collected consists of daily concrete demand, daily aggregate ordered, daily sand ordered, and daily cement ordered on the time frame of one year for 2014 E.C. And related materials costs are collected on each quarter of the year. The data sources were observation and document screening (financial reports and cost breakdown of materials). The summary of the data collected is presented in Annexes.

4.2.2 Data Preprocessing

Since the EOQ analysis is done for raw materials of concrete, the data has been divided into three categories. This is mainly because highly consumed materials used for the production of concrete are Aggregate, Sand, and Cement.

In batching plants, the production rate of concrete is measured in m^3/hr. Typically, batching plants place orders for raw materials based on the demand for concrete as well as the rate at which concrete is produced. The data collected for this research is daily for the year of 2014 E.C., but the time cycle for doing calculations was chosen weekly in this study because from the collected data of this research, we can’t always get a whole year daily demand rate in batching plants (due to holidays off) and this makes it difficult to optimize the raw material size and volume of reservoirs, so, even if demand rate is different at various times of the year, weekly data analysis for this research gives non-zero EOQ results for the whole 52 weeks of the year. Additionally, the length of delivery of raw materials in ready-mixed concrete batching plants is variable from time to time, due to the locations of different suppliers, weekly time cycle data analysis is also best to estimate the reorder point of raw materials. The summary of the data collected weekly is presented in Table 7, for each of the raw materials and concrete.

Table 7. Summary of the demand collected data in a weekly time cycle.

Week	Concrete (m^3)	Aggregate (m^3)	Sand (m^3)	Cement (Quintals)
Week 1	257.3	271.17	185.35	975.66
Week 2	118	124.36	85	447.45
Week 3	335.5	353.59	241.69	1272.19
Week 4	139	146.49	100.13	527.08
Week 5	261	275.07	188.02	989.69
Week 6	160.5	169.15	115.62	608.6
Week 7	208	219.21	149.84	788.72
Week 8	267.5	281.92	192.7	1014.34
Week 9	434.5	457.92	313	1647.59
Week 10	79.5	83.79	57.27	301.46

Week	Concrete (m^3)	Aggregate (m^3)	Sand (m^3)	Cement (Quintals)
Week 11	398	419.46	286.71	1509.19
Week 12	407	428.94	293.19	1543.31
Week 13	331.95	349.84	239.13	1258.73
Week 14	535.95	564.84	386.09	2032.28
Week 15	576.05	607.1	414.97	2184.34
Week 16	580.5	611.79	418.18	2201.21
Week 17	559.5	589.66	403.05	2121.58
Week 18	544.5	573.85	392.24	2064.7
Week 19	723.5	762.5	521.19	2743.46
Week 20	541.5	570.69	390.08	2053.33
Week 21	791	833.64	569.82	2999.41
Week 22	329	346.74	237	1247.54
Week 23	688.5	725.62	495.98	2610.74
Week 24	583	614.43	419.98	2210.69
Week 25	673	709.28	484.81	2551.96
Week 26	683	719.82	492.02	2589.88
Week 27	284	299.31	204.59	1076.91
Week 28	664.5	700.32	478.69	2519.73
Week 29	749	789.38	539.56	2840.15
Week 30	560.5	590.72	403.77	2125.37
Week 31	825	869.47	594.31	3128.34
Week 32	528.5	556.99	380.72	2004.03
Week 33	766	807.29	551.81	2904.61
Week 34	172.5	181.8	124.26	654.11
Week 35	649	683.99	467.52	2460.96
Week 36	691	728.25	497.78	2620.22
Week 37	391.5	412.61	282.03	1484.54
Week 38	467.5	492.7	336.78	1772.72
Week 39	366.5	386.26	264.02	1389.74
Week 40	439	462.67	316.24	1664.65
Week 41	394	415.24	283.83	1494.02
Week 42	47.5	50.06	34.22	180.12
Week 43	309.4	326.08	222.88	1173.22
Week 44	254.6	268.33	183.41	965.42
Week 45	503	530.12	362.35	1907.34
Week 46	842	887.39	606.56	3192.8
Week 47	860	906.36	619.52	3261.05
Week 48	1116.5	1176.69	804.3	4233.68
Week 49	604.5	637.09	435.47	2292.22

Week	Concrete (m^3)	Aggregate (m^3)	Sand (m^3)	Cement (Quintals)
Week 50	860	906.36	619.52	3261.05
Week 51	637.5	671.87	459.24	2417.35
Week 52	351.5	370.45	253.21	1332.86
Total	**25541.8**	**26918.67**	**18399.7**	**96852.34**

4.2.3 EOQ model output analysis

For the analysis of the EOQ model, input data of demand, ordering cost, and holding cost of raw materials are required. And here below listed the inputs used for the model:

Demand: the demands for each raw material are summarized weekly in Table 7.

Ordering Cost: - According to Waters, D. (1992), ordering cost is the price of placing a repeat order for the item and may include allowance for drawing up an order (with checking, acquiring authorization, clearance, and distribution), correspondence and phone costs, receiving (with unloading, checking, and testing), supervision, equipment use, and follow-up. The price of the reorder may occasionally include expenses for things like quality assurance, shipping, delivery, sorting, and moving received products. So, for this research ordering costs are collected from document screening of financial reports from a selected concrete batching plant.

Table 8. Yearly Expenses of selected concrete batching plant for ordering cost of raw materials.

Employee	Yearly Expense (ETB)	Employee	Yearly Expense (ETB)
Loader operator	152, 031.95	Laboratory Tech.	114,067.69
Ass/loader operator	31,249.01	Ass/Lab. Tech.	66,137.85
Bulk load operator	276,182.83	P/supply head	72,405.27
Ass/bulk load operator	122,284.19	P/purchaser	78,148.32
Ass/Transport coordinator	78,335.51	P/store keeper	85,968.98
Senior Lab. Tech.	110,003.12	Ass/store	16,380.62
Yearly Expense Total **= 1,203,195.34 ETB**		Yearly Expense for Each Raw material = **401,065.11 ETB**	

Weekly Expense for each of Raw materials to order = **7712.79 ETB** *(Weekly Expense used to calculate ordering cost per item order)*

ordering cost does not include the unit cost of materials it is a cost that is expensed to order per one truck item(volume)

Truck Volume per order of Aggregate = 16 m^3

Truck Volume per order of Sand = 16 m^3

Truck Volume per order of Cement = 408 Quintals

- ***No of order*** **=** *Weekly Quantity Demand / Truck Volume per order*
- ***Ordering Cost*** **=** *Weekly Expense / No of order*

Holding Cost: - This is the cost of holding one unit of an item in stock for one period of time. It is difficult to suggest values of holding cost, but one view has percentages of unit cost, as:

Table 9. Estimation of holding cost using the cost of the materials. (Waters, D. 1992).

	% of unit cost
Cost of money	10 – 15
Storage space	2 – 5
Loss	4 – 6
Handling	1 – 2
Administration	1 – 2
Insurance	1 – 5
Total	19 – 25

For this research, 20% unit cost of raw materials is chosen for estimating the holding cost, and the unit cost of each raw material is collected from document screening of cost breakdown report from Addis Ababa City Administration Construction Bureau (AACACB) for each quarter of the year 2014 E.C.

Table 10. Summary of collected data for the unit cost of raw materials in each quarter.

Raw Materials	**A quarter of the year for 2014**			
	1st Quarter Cost (ETB)	2nd Quarter Cost (ETB)	3rd Quarter Cost (ETB)	4th Quarter Cost (ETB)
Aggregate	875/m^3	875/m^3	1031.25/m^3	1043.48/m^3
Sand	906.25/m^3	906.25/m^3	1031.25/m^3	1050/m^3
Cement	1057.5/Qui.	1057.5/Qui.	911.25/Qui.	585.72/Qui.

Using the above input data EOQ model computations were done easily as summarized for each of the raw materials in Table 11.

Table 11. The EOQ model outputs for each of the raw materials.

Week	**Concrete Demand (m^3 /week)**	**Aggregate**			**Sand**			**Cement**		
		Demand (m^3/week)	EOQ	ROP	Demand (m^3 /week)	EOQ	ROP	Demand (Qui./week)	EOQ	ROP
Week 1	257.3	271.17	37.5	38.74	185.35	36.26	26.48	975.66	154.01	110.12
Week 2	118	124.36	37.02	17.77	85	38.04	12.14	447.45	180.65	11.11
Week 3	335.5	353.59	37.64	12.87	241.69	37.03	34.53	1272.19	175.87	17.63
Week 4	139	146.49	37.88	20.93	100.13	37.69	14.3	527.08	138.64	87.25
Week 5	261	275.07	37.77	39.3	188.02	36.52	26.86	989.69	155.12	113.92

Week	Concrete Demand (m^3 /week)	Aggregate			Sand			Cement		
		Demand (m^3/week)	EOQ	ROP	Demand (m^3 /week)	EOQ	ROP	Demand (Qui./week)	EOQ	ROP
Week 6	160.5	169.15	36.82	24.16	115.62	37.49	16.52	608.6	148.98	111.85
Week 7	208	219.21	37.15	31.32	149.84	37.64	21.41	788.72	169.59	168.43
Week 8	267.5	281.92	37.16	3.12	192.7	36.97	27.53	1014.34	157.04	120.65
Week 9	434.5	457.92	37.31	28.11	313	36.5	8.22	1647.59	173.32	186.14
Week 10	79.5	83.79	38.43	11.97	57.27	34.91	8.18	301.46	148.28	129.2
Week 11	398	419.46	37.71	22.21	286.71	36.82	4.14	1509.19	165.89	149.14
Week 12	407	428.94	37.42	23.86	293.19	37.23	4.65	1543.31	167.75	158.17
Week 13	331.95	349.84	37.44	12.54	239.13	36.83	34.16	1258.73	174.93	14.66
Week 14	535.95	564.84	37.72	42.98	386.09	37	18.15	2032.28	192.5	100.98
Week 15	576.05	607.1	37.53	11.68	414.97	36.86	22.43	2184.34	162.95	121.4
Week 16	580.5	611.79	37.67	12.06	418.18	37	22.74	2201.21	163.58	125.49
Week 17	559.5	589.66	37.48	9.28	403.05	37.04	20.54	2121.58	160.59	106.3
Week 18	544.5	573.85	37.48	44.49	392.24	36.54	19.49	2064.7	173.54	17.15
Week 19	723.5	762.5	37.42	34.09	521.19	36.66	37.79	2743.46	169.07	161.35
Week 20	541.5	570.69	37.38	44.15	390.08	37.19	18.53	2053.33	173.07	14.67
Week 21	791	833.64	37.59	43.91	569.82	36.7	8	2999.41	165.36	127.92
Week 22	329	346.74	37.27	12.26	237	36.67	33.86	1247.54	174.15	12.2
Week 23	688.5	725.62	37.7	28.26	495.98	36.9	33.95	2610.74	164.93	129.31
Week 24	583	614.43	37.75	12.27	419.98	37.08	22.92	2210.69	163.93	127.8
Week 25	673	709.28	37.7	25.94	484.81	37.09	32.17	2551.96	163.06	115.32
Week 26	683	719.82	37.55	27.73	492.02	36.75	33.54	2589.88	164.27	124.33
Week 27	284	299.31	34.32	8.43	204.59	34.31	29.23	1076.91	174.31	112.92
Week 28	664.5	700.32	34.5	31.04	478.69	34.55	33.84	2519.73	188.53	137.22
Week 29	749	789.38	34.71	8.63	539.56	34.45	8.18	2840.15	185.31	105.32
Week 30	560.5	590.72	34.56	15.28	403.77	34.76	22.93	2125.37	173.15	45.11
Week 31	825	869.47	34.7	20.1	594.31	34.66	15.58	3128.34	181.93	67.22
Week 32	528.5	556.99	34.5	10.57	380.72	34.44	19.94	2004.03	184.18	122.13
Week 33	766	807.29	34.75	11.08	551.81	34.84	9.15	2904.61	187.41	120.4
Week 34	172.5	181.8	35.16	25.97	124.26	34.08	17.75	654.11	166.38	113.95
Week 35	649	683.99	34.49	28.73	467.52	34.72	32.07	2460.96	186.32	123.09
Week 36	691	728.25	34.41	35.22	497.78	34.65	36.46	2620.22	177.99	54.98
Week 37	391.5	412.61	34.45	24.49	282.03	34.23	6.06	1484.54	177.24	104.52
Week 38	467.5	492.7	34.48	35.91	336.78	34.63	13.48	1772.72	173.23	66.82
Week 39	366.5	386.26	34.69	20.49	264.02	34.08	3.64	1389.74	171.48	81.15
Week 40	439	462.67	34.34	31.76	316.24	34.08	11.1	1664.65	234.1	11.14
Week 41	394	415.24	34.36	24.96	283.83	34.03	6.51	1494.02	221.77	196.75
Week 42	47.5	50.06	35.12	7.15	34.22	35.45	4.89	180.12	154.01	77.19
Week 43	309.4	326.08	34.71	11.87	222.88	34.2	31.84	1173.22	226.93	48.95
Week 44	254.6	268.33	34.16	4.18	183.41	35	26.2	965.42	205.85	2.05
Week 45	503	530.12	34.46	41.27	362.35	34.02	17.75	1907.34	224.12	145.06

Week	Concrete Demand (m^3 /week)	Aggregate			Sand			Cement		
		Demand (m^3/week)	EOQ	ROP	Demand (m^3 /week)	EOQ	ROP	Demand (Qui./week)	EOQ	ROP
Week 46	842	887.39	34.53	23.17	606.56	34.24	18.17	3192.8	229.25	222.11
Week 47	860	906.36	34.28	26.63	619.52	34.16	20.19	3261.05	231.68	7.5
Week 48	1116.5	1176.69	34.28	30.97	804.3	34.37	11.78	4233.68	225.12	13.44
Week 49	604.5	637.09	34.31	22.39	435.47	34.42	27.79	2292.22	224.29	85.21
Week 50	860	906.36	34.28	26.63	619.52	34.16	20.19	3261.05	231.68	7.5
Week 51	637.5	671.87	34.39	27.21	459.24	34.11	31.5	2417.35	230.33	114.68
Week 52	351.5	370.45	34.5	18.42	253.21	34.1	36.17	1332.86	209.47	152.28
	25541.75	**26918.67**			**18399.65**			**96852.34**		

Lead Time (LT) of raw materials are (LT aggregate = 1 day(0.14 week), LT sand = 1 day (0.14 week), and LT cement = 3 days (0.43 week))

The output results of the EOQ model are used for the analysis of EOQ based Artificial Neural Network model for the prediction of the optimal order quantity and reordering point of the raw material. And then, the optimal number and size of the raw material reservoirs of batching plants can be estimated. The analysis part for the ANN model will be discussed in detail in the next section

4.3 Analysis of the Artificial Neural Networks Model

One of the objectives of this research is the prediction of the EOQ of raw materials in the ready-mixed concrete batch plant to evaluate the optimal order quantity and reorder point of raw materials, which will be used to evaluate the optimal number and size of reservoirs used for the raw materials. Artificial Intelligence techniques that are represented by Artificial Neural Networks (ANN), were used as a tool for modeling EOQ-based predictions of raw materials that are used for concrete production (Aggregate, Sand, and Cement). Two of the accuracy measurements, correlation coefficient (R) and mean absolute error (MAE), which WEKA 3.8.6 tool used as accuracy measurements are selected to develop the model and to make a comparison between the actual and predicted EOQ of raw materials.

4.3.1 Data Preprocessing

In this section outliers of data, data normalization, and data splitting of the research will be discussed.

Outliers of Data on the Research

The removal of outliers from the data set is controversial, some have opined that the removal of outlier's results in a best-fit model, while others argue the removal of outliers from the data set violates the purpose of the model. However, this research considered outliers removal, because prediction tools like Artificial Neural Network (ANN) need outlier-free data set to achieve better generalization of the network as errors in the data set hinder the modeling process and produce misleading results.

Accordingly, the study carried out data cleaning using Inter Quartile Range (IQR), which is internally supported by the ANN tool, WEKA 3.4.6, to remove outliers from the data set. As a result, there are 3 outliers for each of the EOQ of raw materials results, which are accounts for 5.77% of data from the total 52 weeks of data sets results, and the outliers of raw materials (EOQ of Aggregate, Sand, and Cement) are observed on Week 2, Week 10, and Week 42. In the case of ROP of raw materials, all data sets have normal results.

Data Transformation

Data do not always come in a form that is immediately suitable for analysis. Data transformation is often carried out on the variables before carrying out the analysis. One of the methods of data transformation which is used in machine learning is data normalization, it is a process of translating data into the range [0, 1] (or any range), this gives equal weights/importance to each variable so that no single variable steers model performance in one direction just because they are a bigger number or have different measurements. For the analysis of the EOQ-based ANN model of this research, a data transformation method of normalization is done, which is internally supported by the ANN tool, WEKA 3.4.6.

Data Splitting

In the Artificial Neural Network machine learning model, data splitting is typically done to avoid overfitting. That is an instance where the Artificial Neural Network model fits its training data too well and fails to reliably fit additional data. The original data in an Artificial Neural Network model is typically taken and split into three sets. The three sets commonly used are the training set, the cross-validation set, and the testing set. The training set is the portion of data used to train the model, the cross-validation set also called model validation set is a data set of examples used to change learning process parameters, and has the goal of ranking the model's accuracy and can help with model selection, whereas the testing set is the portion of data that is tested in the final model and is compared against the previous sets of data and used as an evaluation of the final model and algorithm (Gillis, 2022).

For this research, a data splitting with no replacement of 60% for the training set, 20% for the cross-validation set, and 20% for the testing set is performed by using WEKA 3.4.6 tool.

4.3.2 ANN Model Output Analysis

To build the EOQ-based ANN predictive models for the raw materials, the processed data is trained by multiple machine learning algorithms and tested for the evaluation of the model, and the tested model is cross-validated for future predictions. As discussed earlier the data is divided into three sets, namely training, testing set, and cross-validation set. And the dataset split was 60 percent of the data for the training set, 20 percent of the data for the training set, and the rest 20 percent of the data for the cross-validation set. After the training set data is trained by different algorithms, it has to be tested by the new inputs. Hence, the test data is applied to the trained models built by different algorithms to crosscheck their performance, and finally, the tested model's ability for predicting new data is validated using a cross-validation dataset. In this section, the analysis of the model is executed with the help of WEKA 3.8.6.

To develop the model, trial, and error practices were carried out to conclude the best structure of the model. As mentioned before the total number of data used for this analysis are 49 weeks for EOQ after the outliers are removed (29 data sets for training (60%), 10 data sets for testing (20%), and 10 data sets for cross-validation (20%)), and for ROP since there are no outliers in the data set the whole 52 weeks of ROP data are used for analysis (31 data sets for training (60%), 10 data sets for testing (20%), and 11 data sets for cross-validation (20%)). There are several ways to determine a good number of hidden neurons. One solution is to train several networks with varying numbers of hidden neurons and select the one that gives the best result. A second solution is, to begin with, a small number of hidden neurons and add more and select the one that gives the best result. This research has developed a model with a small number of hidden neurons and added more and select the one that gives the highest correlation coefficient (R) and minimum absolute error (MAE).

Using the above input data and procedures EOQ-based ANN models were done for each of the raw materials and summarized here below.

1. ANN Predictive Analysis for EOQ of Aggregate

The Training set for EOQ of Aggregate (29 datasets (60%)

The summary analysis output results of the trials and errors of the artificial neural network for the training sets of EOQ of Aggregate are shown in Table 12 and Table 13.

Table 12. Multilayer Perceptron Neural Network results for one hidden layer of training sets.

No of Neurons	Correlation coefficient	Mean Absolute Error
2 Neurons	0.991	0.2115
3 Neurons	0.991	0.2222
4 Neurons	0.9907	0.2315
5 Neurons	0.9908	0.2344

Table 13. Multilayer Perceptron Neural Network results for two hidden layers of training sets.

1st Layer	2nd Layer	Correlation coefficient	Mean Absolute Error
2 Neurons	1 Neuron	0.9901	0.1786
"	2 Neurons	0.9902	0.1976
"	**3 Neurons**	**0.99**	**0.1744**
"	4 Neurons	0.9902	0.1992
3 Neurons	1 Neuron	0.9903	0.194
"	2 Neurons	0.9902	0.1979
"	3 Neurons	0.9901	0.1988
"	4 Neurons	0.9901	0.1998
4 Neurons	1 Neuron	0.9903	0.1939
"	2 Neurons	0.9897	0.2374
"	3 Neurons	0.9901	0.2001
"	4 Neurons	0.99	0.2008

The MLP-NN models of Training set for EOQ of Aggregate fit data sets with two hidden layers of two and three hidden neurons respectively in the first and second hidden layers with a Correlation Coefficient value of 0.99 and a Mean Absolute Error value of 0.1744.

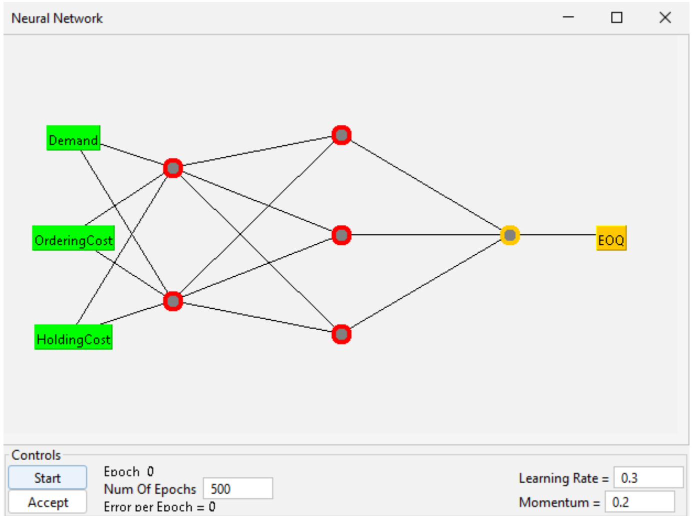


Figure 10: Weka neural network structure of Training set for EOQ of Aggregate.

The above Figure 10, shows the analysis best learning output structure of the neural network for the EOQ of aggregate.

The Testing set for EOQ of Aggregate (10 datasets (20%)

The summary analysis output results of the trials and errors of the artificial neural network for the testing sets of EOQ of Aggregate are shown in Table 14 and Table 15.

Table 14. Multilayer Perceptron Neural Network results for one hidden layer of testing sets.

No of Neurons	Correlation coefficient	Mean Absolute Error
2 Neurons	0.9767	0.3915
3 Neurons	0.975	0.4817
4 Neurons	0.9753	0.5288
5 Neurons	0.9751	0.536

Table 15. Multilayer Perceptron Neural Network results for two hidden layers of testing sets.

1st Layer	2nd Layer	Correlation coefficient	Mean Absolute Error
2 Neurons	1 Neuron	0.9789	0.3122
"	2 Neurons	0.9765	0.2961
"	3 Neurons	0.9803	0.3065
"	4 Neurons	0.9781	0.2939
3 Neurons	1 Neuron	0.9758	0.2974
"	2 Neurons	0.9773	0.296
"	3 Neurons	0.9784	0.2943
"	4 Neurons	0.9792	0.2933
4 Neurons	1 Neuron	0.9761	0.2974

"	2 Neurons	0.9827	0.5665
"	3 Neurons	0.9792	0.2944
"	**4 Neurons**	**0.98**	**0.2935**

The MLP-NN models of the testing set for EOQ of Aggregate fit data sets with two hidden layers of four and four hidden neurons respectively in the first and second hidden layers with a Correlation Coefficient value of 0.98 and a Mean Absolute Error value of 0.2935.

And the analysis best learning neural network output structure for the testing set of the EOQ of aggregate is shown in Figure 11.

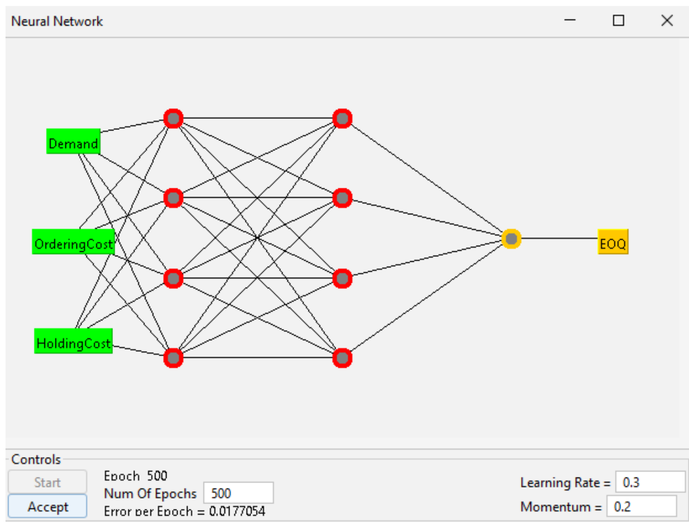


Figure 11: Weka neural network structure of testing set for EOQ of Aggregate.

2. ***ANN Predictive Analysis for EOQ of Sand***

The Training set for EOQ of Sand (29 datasets (60%)

The summary analysis output results of the trials and errors of the artificial neural network for the training sets of EOQ of Sand are shown in Table 16 and Table 17.

Table 16. Multilayer Perceptron Neural Network results for one hidden layer of training sets.

No of Neurons	Correlation coefficient	Mean Absolute Error
2 Neurons	**0.9907**	**0.1318**
3 Neurons	0.9902	0.1317
4 Neurons	0.9902	0.1344
5 Neurons	0.9903	0.1325

Table 17. Multilayer Perceptron Neural Network results for two hidden layers of training sets.

1st Layer	2nd Layer	Correlation coefficient	Mean Absolute Error
2 Neurons	1 Neuron	0.984	0.2026
"	2 Neurons	0.9839	0.2023
"	3 Neurons	0.9849	0.1949
"	4 Neurons	0.9899	0.1423
3 Neurons	1 Neuron	0.984	0.1991
"	2 Neurons	0.9903	0.1377
"	3 Neurons	0.9845	0.1969
"	4 Neurons	0.9905	0.1348
4 Neurons	1 Neuron	0.9892	0.1546
"	2 Neurons	0.984	0.2012
"	3 Neurons	0.9901	0.1403
"	4 Neurons	0.9892	0.1569

The MLP-NN models of the training set for EOQ of Sand fit data sets with one hidden layer of two hidden neurons, with a Correlation Coefficient value of 0.9907 and a Mean Absolute Error value of 0.1318.

And the analysis best learning neural network output structure for the training set of the EOQ of Sand is shown in Figure 12.

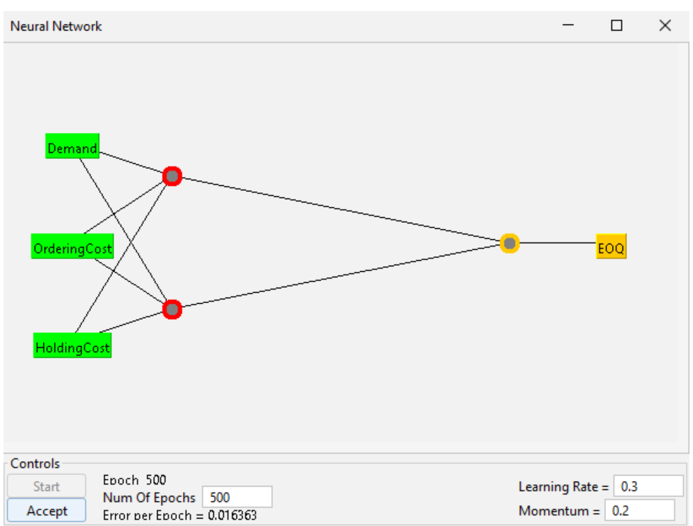


Figure 12: Weka neural network structure of Training set for EOQ of Sand.

The Testing set for EOQ of Sand (10 datasets (20%)

The summary analysis output results of the trials and errors of the artificial neural network for the testing sets of EOQ of Sand are shown below in Table 18 and Table 19.

Table 18. Multilayer Perceptron Neural Network results for one hidden layer of testing sets.

No of Neurons	Correlation coefficient	Mean Absolute Error
2 Neurons	0.9813	0.512
3 Neurons	0.9752	0.5366
4 Neurons	0.9748	0.5459
5 Neurons	0.9704	0.5627

Table 19. Multilayer Perceptron Neural Network results for two hidden layers of testing sets.

1st Layer	2nd Layer	Correlation coefficient	Mean Absolute Error
2 Neurons	1 Neuron	0.9761	0.5628
"	2 Neurons	0.9766	0.4384
"	3 Neurons	0.9791	0.3792
"	4 Neurons	0.9825	0.4209
3 Neurons	1 Neuron	0.9766	0.4648
"	2 Neurons	0.9823	0.4468
"	3 Neurons	0.9774	0.3962
"	**4 Neurons**	**0.9831**	**0.418**
4 Neurons	1 Neuron	0.9827	0.405
"	2 Neurons	0.9707	0.6034
"	3 Neurons	0.9817	0.4412
"	4 Neurons	0.9819	0.3933

The MLP-NN models of the testing set for EOQ of Sand, fit data sets with two hidden layers of three and four hidden neurons respectively in the first and second hidden layers, with a Correlation Coefficient value of 0.9831 and a Mean Absolute Error value of 0.418.

And the analysis best learning neural network output structure for the testing set of the EOQ of Sand is shown in Figure 13.

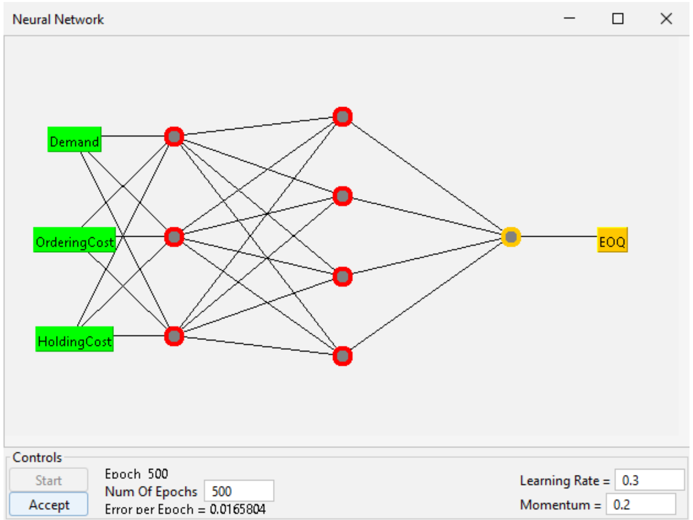


Figure 13: Weka neural network structure of testing set for EOQ of Sand.

3. ***ANN Predictive Analysis for EOQ of Cement***

The Training set for EOQ of Cement (29 datasets (60%)

The summary analysis output results of the trials and errors of the artificial neural network for the training sets of EOQ of Cement are shown in Table 20 and Table 21.

Table 20. Multilayer Perceptron Neural Network results for one hidden layer of training sets.

No of Neurons	Correlation coefficient	Mean Absolute Error
2 Neurons	0.9905	8.0335
3 Neurons	**0.9976**	**2.3304**
4 Neurons	0.9964	4.3144
5 Neurons	0.9975	3.1616

Table 21. Multilayer Perceptron Neural Network results for two hidden layers of training sets.

1st Layer	2nd Layer	Correlation coefficient	Mean Absolute Error
2 Neurons	1 Neuron	0.9859	7.8193
"	2 Neurons	0.9864	7.8268
"	3 Neurons	0.9862	8.0346
"	4 Neurons	0.9599	12.8141
3 Neurons	1 Neuron	0.9715	11.2522
"	2 Neurons	0.9592	13.4917
"	3 Neurons	0.9612	13.1274
"	4 Neurons	0.977	9.9066
4 Neurons	1 Neuron	0.9631	12.9466
"	2 Neurons	0.9643	11.6161

"	3 Neurons	0.9676	11.2359
"	4 Neurons	0.962	12.336

The MLP-NN models of the training set for EOQ of Cement fit data sets with one hidden layer of three hidden neurons, with a Correlation Coefficient value of 0.9976 and a Mean Absolute Error value of 2.3304.

And the analysis best learning neural network output structure for the training set of the EOQ of Cement is shown in Figure 14.

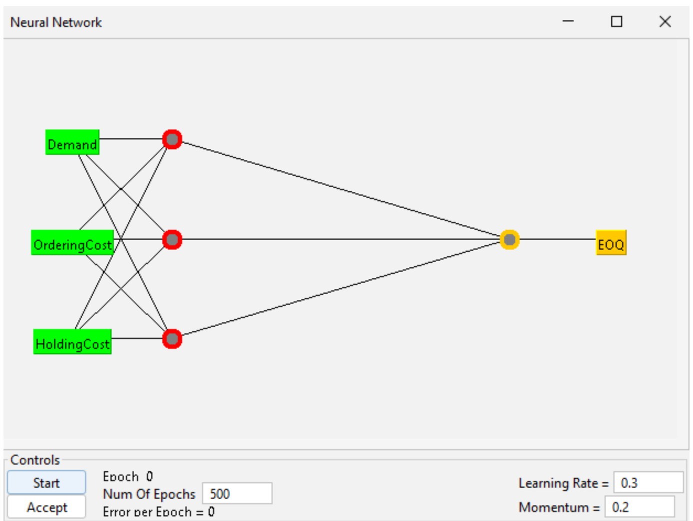


Figure 14: Weka neural network structure of Training set for EOQ of Cement.

<u>The Testing set for EOQ of Cement (10 datasets (20%)</u>

The summary analysis output results of the trials and errors of the artificial neural network for the testing sets of EOQ of Cement are shown in Table 22 and Table 23.

Table 22. Multilayer Perceptron Neural Network results for one hidden layer of testing sets.

No of Neurons	Correlation coefficient	Mean Absolute Error
2 Neurons	0.9931	2.3632
3 Neurons	0.9944	1.8889
4 Neurons	0.9944	1.8732
5 Neurons	**0.9951**	**1.6512**

Table 23. Multilayer Perceptron Neural Network results for two hidden layers of testing sets.

1st Layer	2nd Layer	Correlation coefficient	Mean Absolute Error
2 Neurons	1 Neuron	0.9941	1.9742
"	2 Neurons	0.9933	2.1969
"	3 Neurons	0.993	2.2749
"	4 Neurons	0.9933	2.2449
3 Neurons	1 Neuron	0.9945	1.9032
"	2 Neurons	0.9936	2.1398
"	3 Neurons	0.9935	2.1675
"	4 Neurons	0.9935	2.173
4 Neurons	1 Neuron	0.9944	1.8201
"	2 Neurons	0.9942	2.0534
"	3 Neurons	0.9934	2.0926
"	4 Neurons	0.9939	2.1042

The MLP-NN models of the testing set for EOQ of Cement fit data sets with one hidden layer of five hidden neurons, with a Correlation Coefficient value of 0.9951 and a Mean Absolute Error value of 1.6512.

And the analysis best learning neural network output structure for the testing set of the EOQ of Cement is shown in Figure 15.

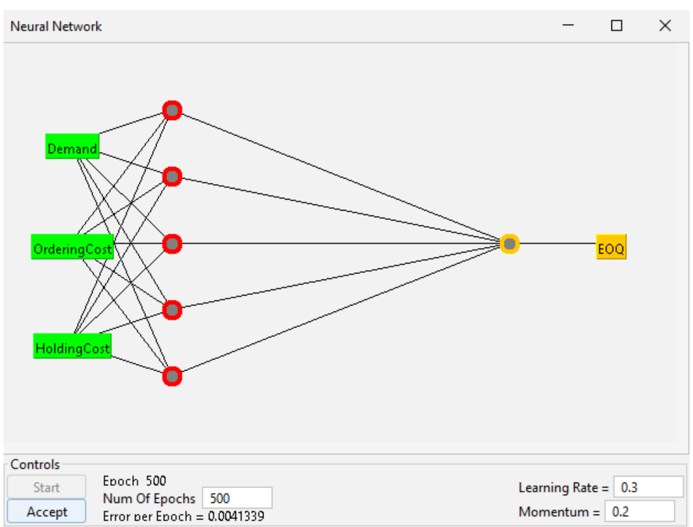


Figure 15: Weka neural network structure of testing set for EOQ of Cement.

4. *ANN Predictive Analysis for ROP of Aggregate, Sand and Cement*

The same steps and procedures as the ANN predictive analysis of EOQ are conducted for the ANN predictive analysis of ROP of Aggregate, Sand, and Cement, and the summary output analysis results that give the best ANN predictive outputs of ROP for training and learning sets are presented in Table 24.

Table 24. Summary of Multilayer Perceptron Neural Network Results for ROP of Aggregate, Sand, and Cement.

Raw Materials ROP	Data Splitting Set	No of Data set	No of Hidden Neurons		Correlation Coefficient	Mean Absolute Error
			1st Layer	2nd Layer		
Aggregate ROP	Training Set	31 (60%)	4	-	0.9982	0.5431
	Testing Set	10 (20%)	4	2	0.9998	0.3621
Sand ROP	Training Set	31 (60%)	4	-	0.9998	0.1647
	Testing Set	10 (20%)	2	-	0.9999	0.1673
Cement ROP	Training Set	31 (60%)	5	-	0.9948	4.5709
	Testing Set	10 (20%)	4	-	0.9828	6.1731

As shown in Table 24, The MLP-NN models of the training set for ROP of Aggregate fit data sets with one hidden layer of four hidden neurons, with a Correlation Coefficient value of 0.9982 and a Mean Absolute Error value of 0.5431 and the testing set for ROP of Aggregate, fit data sets with two hidden layers of four and two hidden neurons respectively in the first and second hidden layers, with a Correlation Coefficient value of 0.9998 and a Mean Absolute Error value of 0.3612.

The MLP-NN models of the training set for ROP of Sand fit data sets with one hidden layer of four hidden neurons, with a Correlation Coefficient value of 0.9998 and a Mean Absolute Error value of 0.1647, and the testing set for ROP of Sand, fit data sets with one hidden layer of four hidden neurons, with a Correlation Coefficient value of 0.9999 and a Mean Absolute Error value of 0.1673.

The MLP-NN models of the training set for ROP of Cement fit data sets with one hidden layer of five hidden neurons, with a Correlation Coefficient value of 0.9948 and a Mean Absolute Error value of 4.5709, and the testing set for ROP of Cement, fit data sets with one hidden layer of four hidden neurons, with a Correlation Coefficient value of 0.9828 and a Mean Absolute Error value of 6.1731.

5. ***EOQ and ROP Artificial Neural Network Predictive model output results for the evaluation of the model using the testing set***

The testing set is a portion of the data set that is tested in the final model and is compared against the previous sets of data, the testing set acts as an evaluation of the final model and algorithm, so for this research after selecting the result of the best fit neural network structure that gives a maximum correlation coefficient and minimum absolute error for each of the raw materials, an evaluation of the model is performed using the best-fit testing sets of raw materials.

ANN Predictive model output for Aggregate EOQ and ROP

For ANN predictive model analysis of aggregate, a best-fit neural network output result is needed for both EOQ and ROP of aggregate. From the previous testing set analysis of aggregate, we have best-fit testing set results of EOQ for Aggregate with two hidden layers of four and four hidden neurons respectively in the first and second hidden layers (having a value of 0.98 Correlation Coefficient, and 0.2935 Mean Absolute Error). And for the ROP of aggregate, we have a best-fit testing set results, with two hidden layers of four and two hidden neurons respectively in the first and second hidden layers used (having a value of 0.9998 Correlation Coefficient, and 0.3621 Mean Absolute Error).

Table 25. Results of ANN predictive model output for Aggregate EOQ and ROP.

Instances	**EOQ**			**ROP**		
	Actual	Predicted	Error	Actual	Predicted	Error
1	37.48	37.692	0.212	23.17	23.433	0.263
2	37.44	**37.731**	0.291	11.97	13.11	1.14
3	37.42	37.718	0.298	7.15	9.217	2.067
4	34.75	34.675	-0.075	25.97	26.243	0.273
5	34.36	35.076	0.716	22.39	23.999	1.609
6	34.69	35.561	0.871	12.27	13.259	0.989
7	37.42	37.669	0.249	12.06	13.218	1.158
8	37.64	**37.731**	0.091	8.43	9.353	0.923
9	37.59	37.662	0.072	8.63	9.292	0.662
10	37.75	37.69	-0.06	27.73	27.184	-0.546

From the results shown in Table 25, a maximum predicted aggregate EOQ of 37.731 m^3 is obtained, this result is used as an input for calculating the maximum ordered amount of aggregate that is used for calculating an optimal volume of aggregate storage reservoirs and an optimal concrete quantity which is used as an input for dispatching model.

Table 26. Results of ANN predictive model output accuracy measurements for Aggregate EOQ and ROP.

	EOQ	**ROP**
Correlation coefficient	0.98	0.9998
Mean absolute error	0.2935	0.3621

The results shown in Table 26, show the ANN predictive model had the highest accuracy for predicting Aggregate EOQ and ROP.

ANN Predictive model output for Sand EOQ and ROP

Inputs used for this analysis are, a best-fit neural network testing set results of EOQ for sand with two hidden layers of three and four hidden neurons respectively in the first and second hidden layers (having a value of 0.9831 Correlation Coefficient, and 0.418 Mean Absolute Error). And for the ROP of sand, we have a best-fit testing set results, with one hidden layer of two hidden neurons (having a value of 0.9999 Correlation Coefficient, and 0.1673 Mean Absolute Error).

Table 27. Results of ANN predictive model output for Sand EOQ and ROP.

Instances	EOQ			ROP		
	Actual	Predicted	Error	Actual	Predicted	Error
1	37.04	37.266	0.226	18.17	18.277	0.107
2	36.83	37.642	0.812	8.18	8.17	-0.01
3	37.23	37.448	0.218	4.89	4.983	0.093
4	34.84	34.662	-0.178	17.75	17.85	0.1
5	34.03	33.72	-0.31	27.79	28.23	0.44
6	34.08	34.088	0.008	22.92	23.029	0.109
7	36.66	37.426	0.766	22.74	22.848	0.108
8	37.03	**37.651**	0.621	29.23	29.381	0.151
9	36.7	37.537	0.837	8.18	8.632	0.452
10	37.08	37.284	0.204	33.54	33.642	0.102

From the results shown in Table 27, a maximum predicted sand EOQ of 37.651 m^3 is obtained, this result is used as an input for calculating the maximum ordered amount of sand that is used for calculating an optimal volume of sand reservoirs and an optimal concrete quantity which is used as an input for dispatching model.

Table 28. Results of ANN predictive model output accuracy measurements for Aggregate EOQ and ROP.

	EOQ	ROP
Correlation coefficient	0.9831	0.9999
Mean absolute error	0.418	0.1673

The results shown in Table 28, show the ANN predictive model had the highest accuracy for predicting Sand EOQ and ROP.

ANN Predictive model output for Cement EOQ and ROP

Inputs used for this analysis are, a best-fit neural network testing set results of EOQ for Cement with one hidden layer of five hidden neurons (having a value of 0.9951 Correlation Coefficient, and 1.6512 Mean Absolute Error). And for the ROP of cement, we have a best-fit testing set results, with one hidden layer of four hidden neurons (having a value of 0.9828 Correlation Coefficient, and 6.1731 Mean Absolute Error).

Table 29. Results of ANN predictive model output for Cement EOQ and ROP.

Instances	EOQ			ROP		
	Actual	Predicted	Error	Actual	Predicted	Error
1	160.59	161.543	0.953	222.11	222.507	0.397
2	174.93	173.679	-1.251	129.2	121.254	-7.946
3	167.75	165.76	-1.99	77.19	73.713	-3.477
4	187.41	185.526	-1.884	113.95	90.004	-23.946
5	221.77	**221.817**	0.047	85.21	87.807	2.597
6	171.48	169.555	-1.925	127.8	123.663	-4.137
7	169.07	167.181	-1.889	125.49	123.168	-2.322
8	175.87	173.847	-2.023	112.92	112.686	-0.234
9	165.36	168.732	3.372	105.32	120.612	15.292
10	163.93	162.754	-1.176	124.33	120.222	-4.108

From the results shown in Table 29, a maximum predicted Cement EOQ of 221.817 Qui. is obtained, this result is used as an input for calculating the maximum ordered amount of cement that is used for calculating an optimal number and volume of cement silos, and an optimal concrete quantity which is used as an input for delivering model.

Table 30. Results of ANN predictive model output accuracy measurements for Aggregate EOQ and ROP.

	EOQ	ROP
Correlation coefficient	0.9951	0.9828
Mean absolute error	1.6512	6.1731

The results shown in Table 30, show the ANN predictive model had the highest accuracy for predicting Cement EOQ and ROP.

Calculation of Input Data Used for Delivering Model Based on the Predicted ANN model output Results

In every Artificial Neural Network simulation, evaluation of the model is done based on the outputs of testing sets, so this research is used the maximum values of predicted testing set value for the evaluation of the ANN model

Table 31. Input data calculation used for the delivering model.

Material	**Max. EOQ** (From MLP-NN result)	**Min. Cycle Time** (From ROP Model)	**Max. Ordered Amount** (Used for Delivery Model)	**Real Max. Demand** (From EOQ Model)	**Remark**
Aggregate	37.731	0.03(34 orders)	37.731*34 =**1282.85**	1176.69 (Week 48)	1282.85>1176.69 ***Ok!***
Sand	37.651	0.04(25 orders)	37.651*25 =**941.28**	804.3 (Week 48)	941.28>804.3 ***Ok!***
Cement	221.817	0.05(20 orders)	221.817*20 =**4436.34**	4233.68 (Week 48)	4436.34>4233.68 ***Ok!***

Since one of the objectives of this research is integrating the EOQ-based ANN prediction model with the DES delivering model, it is expected to change the ANN predictive raw material maximum ordered amount to concrete by the ratio of raw materials demand to concrete demand, to get an input entity used for concrete delivering model. To do this, the company's overall yearly demand for concrete, aggregate, sand, and cement is listed below, then calculate the ratio of each raw material to concrete and find the maximum concrete quantity for delivering model analysis.

Table 32. Conversion of raw materials to concrete.

	Demand	**Ratios to Concrete**	**Max Ordered Amount**	**Converted to Concrete**	**Remark**
Concrete	25541.75 m^3	**1**			
Aggregate	26918.67 m^3	26918.67/25541.75 =**1.054**	1282.85	1282.85/1.054 =**1217.13**	
Sand	18399.64 m^3	18399.64/25541.75 =**0.720**	941.28	941.28/0.720 =**1307.33**	***Max. Ok!***
Cement	96852.34 Qui.	96852.34/25541.75 =**3.792**	4436.34	4436.34/3.792 =**1169.92**	

The result shown in Table 32, shows that a maximum converted concrete is obtained using sand maximum ordered amount and the converted amount is greater than the maximum concrete quantity that the batching plant delivered to sites which are on week 48 of the data set, Therefore, for the analysis of delivering model a concrete quantity of **1307.33 m^3** is used because higher consumption or delivery of concrete quantity shows an optimal quantity of the batching plant production. So using the higher consumption concrete quantity in that year, optimization of productivity rate and resource utilization for delivery of concrete to sites are performed using DES analysis and the result will give the optimal number of trucks that will be needed by the batching plant for delivering concrete to sites and gives the productivity rate of truck and mixer.

1307.33 m^3 > 1116.5 m^3 (week 48) ………. *Ok!*

<u>Batching plant raw materials reservoirs estimations using ANN predictive model outputs</u>

Table 33. Reduction in Batching Plant Reservoirs Capacity based on ANN Predictive Model

Raw Materials	Real Batching Plant Reservoirs Capacity (m^3)	ANN Model Estimated Reservoirs Capacity (m^3) *(From Table 30)*	Reservoirs Reduction %age.
Aggregate	3500	1282.85	**63.35 %**
Sand	4500	941.28	**76.47 %**
Raw Material	**Real Batching Plant Reservoirs Capacity (Qui.)**	**ANN Model Estimated Reservoirs Capacity (Qui.) *(From Table 31)***	**Reservoirs Reduction %age.**
Cement	5000	4436.36	**11.27 %**

From the results shown in Table 33, based on ANN predictive model output results there is a percentage reduction of reservoir capacity for aggregate, sand, and cement with a percentage of 63.35%, 76.47%, and 11.27% respectively. So this study is trying to minimize the batching plant reservoir capacity with the percentage values listed above, which is one of the objectives of this study.

4.3.3 ANN model validation

Model validation is the process used to evaluate the trained model using testing data after model training. The testing data may or may not be a portion of the same data set from which the training set is obtained. But this study used a dataset that had no replacement for the training, testing, and cross-validation sets. There are two categories of model validation techniques:

In-sample validation – testing data from the same dataset that is used to build the model.

Out-of-sample validation – testing data from a new dataset that isn't used to build the model.

This study also employed of sample validation technique using a cross-validation method, which is a machine-learning evaluation technique that determines how well a machine-learning model can forecast the outcome of unseen data. It's also a method that's simple to understand, performs well with a small data sample, and also provides a less biased evaluation, making it a popular option.

This research is conducted a k-fold cross-validation technique which is internally supported by WEKA 3.8.6 tool, the data sample is split into a 'k' number of smaller samples, hence the name: K-fold Cross Validation. Choosing a good value for k is important. A poor value for k can result in a poor evaluation of the model's abilities. In other words, it can cause the measured ability of the model to be overestimated (high bias) (Nellihela 2022).

Hence the ultimate goal for any machine learning model is to learn from examples in such a manner that the model is capable of generalizing the learning to new instances that it has not yet seen. So this research also validated the ANN Predictive model using the k-fold cross-validation technique for evaluating the ability of a machine learning model to predict new data that have not been seen, and the summarized EOQ and ROP k-fold cross-validation results for each raw material are described below in the tables.

Cross-Validation set for EOQ of Aggregate (10 datasets (20%)

Check for the k-folds value

Table 34. Summary of k-fold values and their results for cross-validation sets.

k-fold Nos	Correlation coefficient	Mean Absolute Error
2	0.9977	0.0811
3	**0.9988**	**0.057**
4	0.9986	0.0644
5	0.9972	0.0924
6	0.9972	0.0923
7	0.9979	0.0828
8	0.997	0.0975
9	0.998	0.0824
10	0.9979	0.0838

The k-fold value of 3 is chosen for the cross-validation set of EOQ of Aggregate which makes the dataset fit with a maximum correlation coefficient of 0.9988 and a minimum absolute error value of 0.057. The results show that the developed model can predict new data.

Cross-Validation set for EOQ of Sand (10 datasets (20%)

Check for the k-folds value

Table 35. Summary of k-fold values and their results for cross-validation sets.

k-fold Nos	Correlation coefficient	Mean Absolute Error
2	0.8568	0.5376
3	**0.9296**	**0.3245**
4	0.9267	0.3599
5	0.8572	0.5069
6	0.8488	0.5288
7	0.867	0.5125
8	0.8468	0.5689
9	0.8505	0.5438
10	0.8973	0.4339

The k-fold value of 3 is chosen for the cross-validation set of EOQ of Sand which makes the dataset fit with a maximum correlation coefficient of 0.9296 and a minimum absolute error value of 0.3245. The results show that the developed model can predict new data.

Cross-Validation set for EOQ of Cement (10 datasets (20%)

Check for the k-folds value

Table 36. Summary of k-fold values and their results for cross-validation sets.

k-fold Nos	Correlation coefficient	Mean Absolute Error
2	0.9103	8.8534
3	0.8368	11.0312
4	0.9378	6.0885
5	0.9306	7.2453
6	0.9311	7.1215
7	0.9315	6.8981
8	0.9362	6.4818
9	**0.9433**	**6.3407**
10	0.8869	8.895

The k-fold value of 9 is chosen for the cross-validation set of EOQ of Cement which makes the dataset fit with a maximum correlation coefficient of 0.9433 and a minimum absolute error value of 6.3407. The results show that the developed model can predict new data.

Cross-Validation set for ROP of Aggregate (11 datasets (20%)

Check for the k-folds value

Table 37. Summary of k-fold values and their results for cross-validation sets.

k-fold Nos	**Correlation coefficient**	**Mean Absolute Error**
2	0.9781	1.8491
3	0.7305	4.8149
4	0.9838	1.567
5	0.9754	1.5696
6	0.9873	1.3634
7	0.9861	1.3868
8	0.986	1.3992
9	0.9884	1.3407
10	0.9822	1.4203
11	**0.9916**	**1.1957**

The k-fold value of 11 is chosen for the cross-validation set of ROP of Aggregate which makes the dataset fit with a maximum correlation coefficient of 0.9916 and a minimum absolute error value of 1.1957. The results show that the developed model can predict new data.

Cross-Validation set for ROP of Sand (11 datasets (20%)

Check for the k-folds value

Table 38. Summary of k-fold values and their results for cross-validation sets.

k-fold Nos	Correlation coefficient	Mean Absolute Error
2	0.9961	0.6663
3	0.984	1.5155
4	0.9943	0.6813
5	0.9926	0.8463
6	0.9924	0.8228
7	0.9919	0.8479
8	0.9966	0.6805
9	0.9946	0.6761
10	**0.996**	**0.5617**
11	0.9958	0.6813

The k-fold value of 10 is chosen for the cross-validation set of ROP of Sand which makes the dataset fit with a maximum correlation coefficient of 0.996 and a minimum absolute error value of 0.5617. The results show that the developed model can predict new data.

Cross-Validation set for ROP of Cement (11 datasets (20%)

Check for the k-folds value

Table 39. Summary of k-fold values and their results for cross-validation sets.

k-fold Nos	Correlation coefficient	Mean Absolute Error
2	0.2148	43.8403
3	0.4148	56.3612
4	0.3740	59.0358
5	0.4377	45.5091
6	0.3826	40.0368
7	0.5008	36.5042
8	0.6578	32.1060
9	0.4538	40.5422
10	0.6875	31.6826
11	**0.8949**	**29.3720**

The k-fold value of 11 is chosen for the cross-validation set of ROP of Cement which makes the dataset fit with a maximum correlation coefficient of 0.8949 and a minimum absolute error value of 29.3720. The results show that the developed model can predict new data.

Conclusion - The developed ANN predictive model can predict new data.

4.4 Develop ANN-based DES model for delivering RMC to sites.

This section provides an explanation of the issues related to the ANN-based DES model, RMC to site delivering process, model development, data collection, and input data analysis, developing Simphony input data analysis, developing and running the simulation model using Simphony CYCLONE software, collecting output data from the simulation that are acquired, and finally establishing the key research findings.

4.4.1 Designing model in sequence and logical manner.

Modeling the RMC-to-site delivery process necessitates an in-depth study and examination of the component practice and issues related to RMC site delivery operations from the sample projects. For this research, 182 RMC-to-site delivery operations or cycles from two sample projects were observed. And, the entire cycle of the observed RMC-to-site delivery procedure is broken down into seven tasks: truck loading, traveling, positioning to dump, dumping, washing at the site, returning, and washing at the plant.

The first step in creating a concrete delivery operation model is identifying the issue and abstracting the total operation process that took place in the real world. This requires the ability to visually depict the entire operation of the process from beginning to end. According to AbouRizk et al. (2015), after a model has been developed, it should be possible to explain the overall workflow of the actual process by simply tracking an entity's path through the model.

Figure 16 shown below, demonstrates the entire schematic of the RMC to-site delivery operation process and describes each cycle from start to finish. The operation process starts with loading the RMC onto a truck (Loading), then the loaded truck travels to the construction site (Traveling), and after arriving at the construction site the truck is positioned and waited to dump (Positioning), it dumps the RMC (dumping) after dumping the truck is washed in the site (Washing at the site), Finally, the truck travels back to the batching plant (Returning) and washed at the plant for another loading (Washing at the plant). So this research is conducted based on the schematic diagrams shown in Figure 16, for the analysis of the ANN-based DES delivery model of RMC to sites.

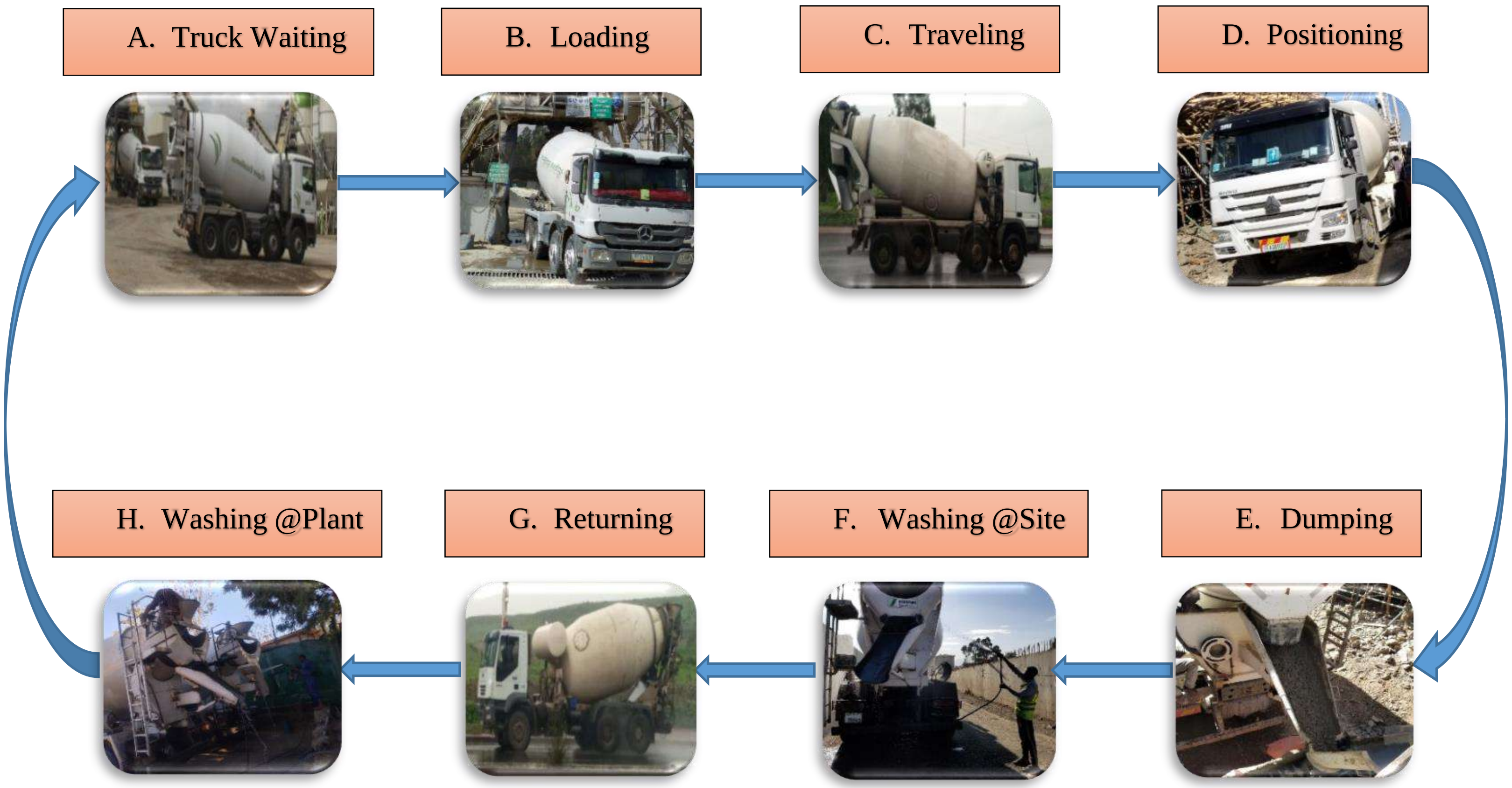


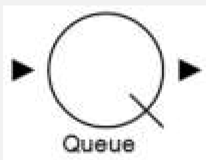
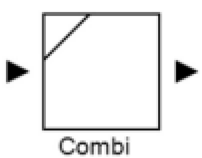
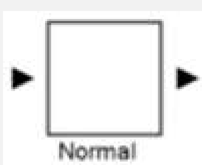
Figure 16: Demonstrates the researched area (Selected batching plant concrete delivery) real observed entire concrete site delivery process operation and describes each task from the start to finish.

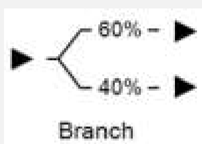
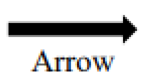
Because of the immense scope of work required and the numerous raw materials and equipment needed, ready-mix concrete production and its delivery process operations are typically categorized as heavy civil works within the construction sector. The fact that there are several interconnected cycles involved in the production of ready-mix concrete and its delivery process activities is another characteristic. Each of the cycles has uncertainty, as depicted in Figure 16. Understanding and abstracting the key components is the first step in modeling and simulating the logical flow, dynamics, and uncertainty of such activities. The key components must then be represented in graphical symbols using simulation software language. Additionally, the development of a simulation model requires the description of input and output parameters that should be collected from the construction site described as input requirement parameters and information that is collected from simulation described as simulation experiment result output.

A suitable software program must be used to simulate the graphical model of the concrete site delivery operation process developed in Figure 16. "Simphony CYCLONE" is the simulation program that was utilized in this study to simulate the operation of delivering concrete.

However, to construct a symbolic simulation model using computer simulation, it is crucial to be familiar with the graphical simulation language. Simphony CYCLONE simulation graphical simulation language is presented and explored below in Table 40.

Table 40. Graphical symbols of elements used to develop a simulation model using SIMPHONY-CYCLONE

No	Entities / Graphical symbol	Entity description	Input data scope	Output data scope	Abstract / Entity representation
1		**Queue/Create Element** •It initializes entities within the model at the beginning of the simulation (creating entities and introducing them into the model) • The input is connected to any type of element except a Queue. The output point of a Queue element may only be connected to Combi elements. • It is a place where entities are waiting for service.	• Total number of entities • The number of entities waiting for service.	• Several entities at the end of the simulation • Statistical report (waiting time, a percentage of waiting)	• At the start of the model. • Number of trucks waiting to dump • Number of trucks waiting to wash at the plant • Number of the crew in dumping • Number of the crew in washing at the plant
2		**Combi/Task Element** • The Combi element represents a constraint. • During simulation, entities can flow into the Combi from preceding queues. The output point may be connected to any type of element except a Combi. • It is responsible for modeling an activity.	• The duration of the activity (time) • The number of servers available for the activity. • Priority of the system	• Statistical report (entity interarrival time)	• Concrete loading and dumping cycle • Truck washing at the plant cycle
3		**Normal/Task Element** • The Normal element can process an infinite number of entities simultaneously, so it represents an unconstrained task. • The input is connected to any type of element except a Queue. The output	• The duration of the task (time)	• Statistical report (entity interarrival time)	• A truck traveling to the construction site cycle • Truck positioning to dump concrete cycle • Truck washing at the site cycle • Truck return to plant site cycle

		point may be connected to any type of element except a Combi. • It is responsible for modeling an activity.			
4		**Counter Element** • Measures production of entities by recording the time an entity passes through it. • The input point may be connected to any type of element except a Queue and the output may be connected to any type of element except a Combi. • The Counter in CYCLONE can also be used to terminate the simulation.	• The amount of the counter should be incremented with each passing entity (entity capacity). • The count value at which the simulation will be terminated. • The count amount at which the simulation will be terminated	• Number of the entity that passes through the counter during simulation, • Simulation time at which the pass observed • Statistical report (entity interarrival time, production, and production rate)	• Productivity of truck • Productivity of Mixer • Productivity of concrete dumping/placing crew • Productivity of the washing crew at the plant • overall Production of the system
5		**The (Probabilistic) Branch Element** • is used to model uncertainty associated with events in systems being modeled • The input point of a Branch element may be connected to any type of element except a Queue. The output points of a Branch element may be connected to any type of element except a Combi.	• The probability that an arriving entity will be routed through the topmost branch. This value must be between 0 and 1.		• Truck traveling and return route (roads). Which route is used mostly Route A, Route B, and Route C?
6		**Arrow Element** • Responsible to show the direction of the work sequence in the model			• Indicate the direction of delivery process flows

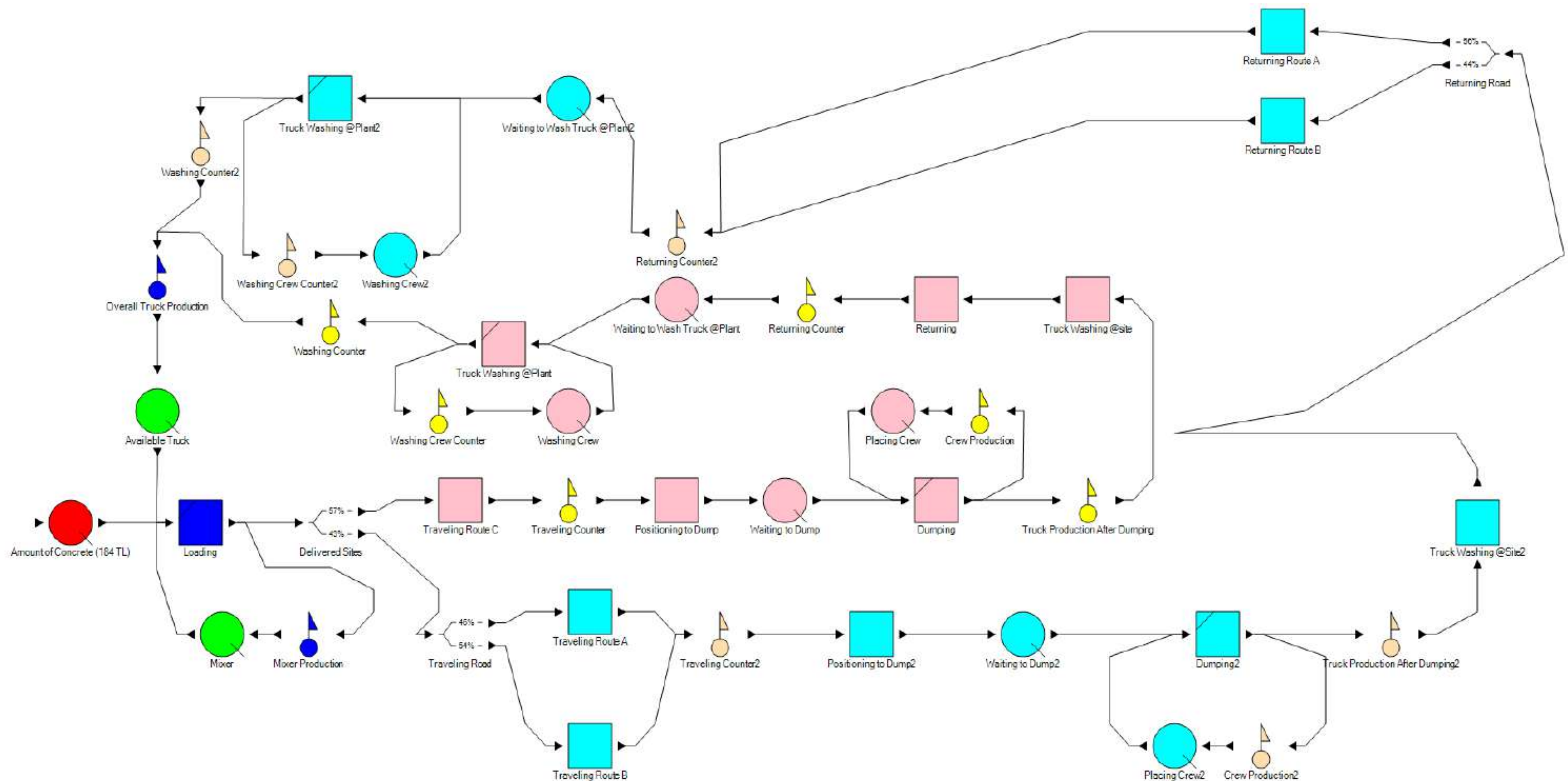


Figure 17: Overall concrete site delivery operation model developed by using Simphony CYCLONE simulation software.

4.4.2 Developing model input data analysis.

The process of designing and creating a simulation model extends beyond just summarizing and representing the complete operation in graphical and abstract symbols. It entails accurately gathering and modeling input data for the model for each cycle, with precisely defined parameters.

(AbouRizk et al.2015; Banks et al. 2001) are recommended four steps in developing useful model input data for any kind of simulation software, namely, collect input data from the real operation, identify appropriate data distribution, estimate distribution parameters, and test for goodness of fit data.

4.4.2.1 Input data collection process.

One of the biggest tasks in resolving a real problem is the process of collecting input data. To build a working environment with real-world operation in the simulation model, real input data from a sample project must be collected for each component or cycle of concrete site delivery operation with a distinct delivery time. This idea is supported by Wang et al. (2001), who argue that to create a useful model, it is essential to first understand the nature of the actual system, this was done through information gathered from the construction site.

The data is discrete (uncertainty) cycle-to-cycle, and the observation process took over from the time intervals of the initial to the finishing of the delivery process. The data collection has been done by classifying the delivery operation which is (loading time, traveling time, positioning to dump time, dumping time, washing at the site time, returning time, and washing at the plant time.) through the consideration of different delivery sites, traffic condition, casting structure, and interruption events. And the collected observed data takes 3 months (04 May/2014 E.C – to – 03/August/2014 E.C) for collecting 182 data from the two sampled projects, which makes the developed model to simulate the most realistic simulation model.

Typically, quantitative sample data from construction sites and batching plants in a variety of conditions was collected through observation and interviews. There were a total of 182 (one hundred eighty-two) cycles or trips of concrete site delivery operation. The compiled input data are summarized in Table 41. The overall report of the data collection is also shown in Annex B.

Table 41. Overall Summary of Observed Data Collected.

Total Delivered Cycle Observed	Overall Summary of Observed Data Collected for Seven Activities on The Full Cycle: Loading – Site 1	Loading – Site 2	Traveling – Route A	Traveling – Route B	Traveling – Route C	Traveling – Traffic Condition – Jam Hour	Traveling – Traffic Condition – Free Hour	Positioning at Site – Site 1	Positioning at Site – Site 2	Dumping – Site 1	Dumping – Site 2	Washing at Site – Site 1	Washing at Site – Site 2	Returning – Route A	Returning – Route B	Returning – Route C	Returning – Traffic Condition – Jam Hour	Returning – Traffic Condition – Free Hour	Washing at Plant – Site 1	Washing at Plant – Site 2	Event Seen in The Cycle – Site 1	Event Seen in The Cycle – Site 2	Event Seen in The Cycle – Note
182	104	78	36	42	104	53	129	104	78	104	78	104	78	34	44	104	66	116	104	78	6	2	Cement Gate Problem

Total Delivered Amount of Concrete – Cycle	Total Delivered Amount of Concrete – m^3	Min. Delivered Concrete in One Cycle (m^3)	Max. Delivered Concrete in One Cycle (m^3)	Avg. Delivered Concrete in One Cycle (m^3)	Casting Structure: Retaining Wall – Cycle	Retaining Wall – %age	Curb Stone – Cycle	Curb Stone – %age	Man Hole – Cycle	Man Hole – %age	U Ditch – Cycle	U Ditch – %age	Type B Curb Stone – Cycle	Type B Curb Stone – %age	Total Cycle
182	1294	3	9.5	7.11	75	41.21	26	14.29	29	15.93	11	6.04	41	22.53	182

Delivery Route Used and Traffic Condition

Traveling – Site	Route	Cycle	%age	Total %age From the Overall Collected Data	Traffic Condition – Jam Hour – Cycle	Jam Hour – %age	Free Hour – Cycle	Free Hour – %age	Total %age – Jam Hour	Total %age – Free Hour	Returning – Site	Route	Cycle	%age	Total %age From the Overall Collected Data	Traffic Condition – Jam Hour – Cycle	Jam Hour – %age	Free Hour – Cycle	Free Hour – %age	Total %age – Jam Hour	Total %age – Free Hour
Site 1	C	104	57.14	57.14	33	18.13	71	39.01	18.13	39.01	Site 1	C	104	57.14	57.14	41	22.53	63	34.61	22.53	34.61
Site 2	A	36	19.78	42.86	18	9.89	18	9.89	10.99	31.87	Site 2	A	34	18.68	42.86	20	10.99	14	7.69	13.74	29.12
	B	42	23.08		2	1.1	40	21.98				B	44	24.18		5	2.75	39	21.43		

SITE 1 is a road project from Bole Homes - Gumruk and SITE 2 is a road project from Sansusi - Tatek Kela

4.4.2.2 Identified an appropriate data distribution.

According to AbouRizk et al. (2015), manually fitting a statistical distribution to sample data can be time-consuming. Utilizing computer software throughout the fitting process simplifies the process. Simphony offers and enables the selection of the best-fitting distributions to sample data based on several parameters.

Simphony software makes it easy to choose the distribution that fits the sample data the best, so it is crucial to understand how it does this. Identifying the suitable data distribution, estimating the distribution parameters, and testing for the Goodness of fit are the three crucial processes in Simphony's data fitting procedure. Each of the data fitting procedures is described below:

I. Identify appropriate data distribution

The simplest method of choosing a statistical distribution for a collection of data is to compare the sample to the theoretical distribution's shape. Since both represent the weight of each sample interval in terms of its probability of occurring, a histogram created from the sample is comparable to the PDF (probability density function) of the theoretical distribution. The goal would be to compare the sample's histogram's shape to the shape of a known distribution. The problem with this technique, however, is the construction of the histogram itself. In the absence of a standard technique to do this, one can easily distort the real shape of the histogram by inappropriately specifying the width of the cells and their locations.

II. Estimating the distribution parameters

The availability of data determines how well one can estimate a given distribution's parameters. To estimate the parameters of the underlying distribution when data are present, one can use moment matching, maximum likelihood, least squares, or other methods. The simulator is recommended to employ all fitting methods available in the software being used and choose the parameters that generate the best fit because different procedures frequently result in different parameter estimates (AbouRizk et al. 2015).

III. Testing for the Goodness of Fit

One should check for the goodness of fit by comparing the fitted distribution to the empirical distribution and analyzing the quality of the fit achieved to determine the acceptability of a proposed input model using the guidance provided by goodness-of-fit tests. The Chi-Square and K-S tests, often known as the Kolmogorov-Smirnov tests, are typically used to conduct the goodness of fit test.

A. Chi-Squared Test

The chi-squared test measures the difference between the sample's histogram and the fitted probability density function. The test rejects the fitted model when the difference is sufficiently large; however, if the fit is good, the discrepancy should be "small" (AbouRizk et al. 2015).

B. The Kolmogorov-Smirnov (K-S) Test

When sample sizes are small and no parameters have been estimated from the data, the Kolmogorov-Smirnov (K-S) test is especially helpful. This test is based on the discrepancy between the empirical cumulative distribution function and the fitted cumulative distribution function (CDF) (Banks et al. 2001). According to AbouRizk et al. (2015), the Kolmogorov-Smirnov test (simply the K-S test) is based on measuring the largest discrepancy between the empirical distribution function defined by the samples and the fitted cumulative distribution function.

However, Simphony can analyze and choose the best-fit distributions to sample observations input data by comparing the statistical goodness-of-fit data to the empirical cumulative density function (CDF) and the fitted (theoretical) CDF. Simphony fits distributions to sample observations using three different methods, including moment matching, maximum likelihood, and least squares. And Chi-square and the Kolmogorov-Smirnov (K-S) tests are used to assess the goodness of fit. For this research, an appropriate distribution can be selected with the help of the Simphony distribution parameter selection method.

4.4.2.3 Simphony CYCLONE input data analyzer best fitting results.

Two file formats are supported by Simphony CYCLONE for the import of data for input modeling. These include text files like Notepad and CSV files, among others. In all situations, the data must be collected in a single column. In addition, when undertaking input modeling, two significant factors need to be taken into consideration. The first has to do with choosing an appropriate method for estimating statistical distributions' parameters to fit the data. The second has to do with choosing a goodness-of-fit test that will help determine which fitted option will yield the best statistical distribution.

It is critical to establish criteria for selecting an appropriate parameter of statistical distribution and criteria for ranking the best goodness-of-fit. Accordingly, for this study, a distribution selection parameter that gives a best-fit statistical distribution is selected for each of the tasks. The other important criterion in selecting the best goodness-of-fit. In line with this, the study has used both Kolmogorov-Smirnov (K-S) and chi-squared test methods of testing goodness-of-fitted for all types of sample data.

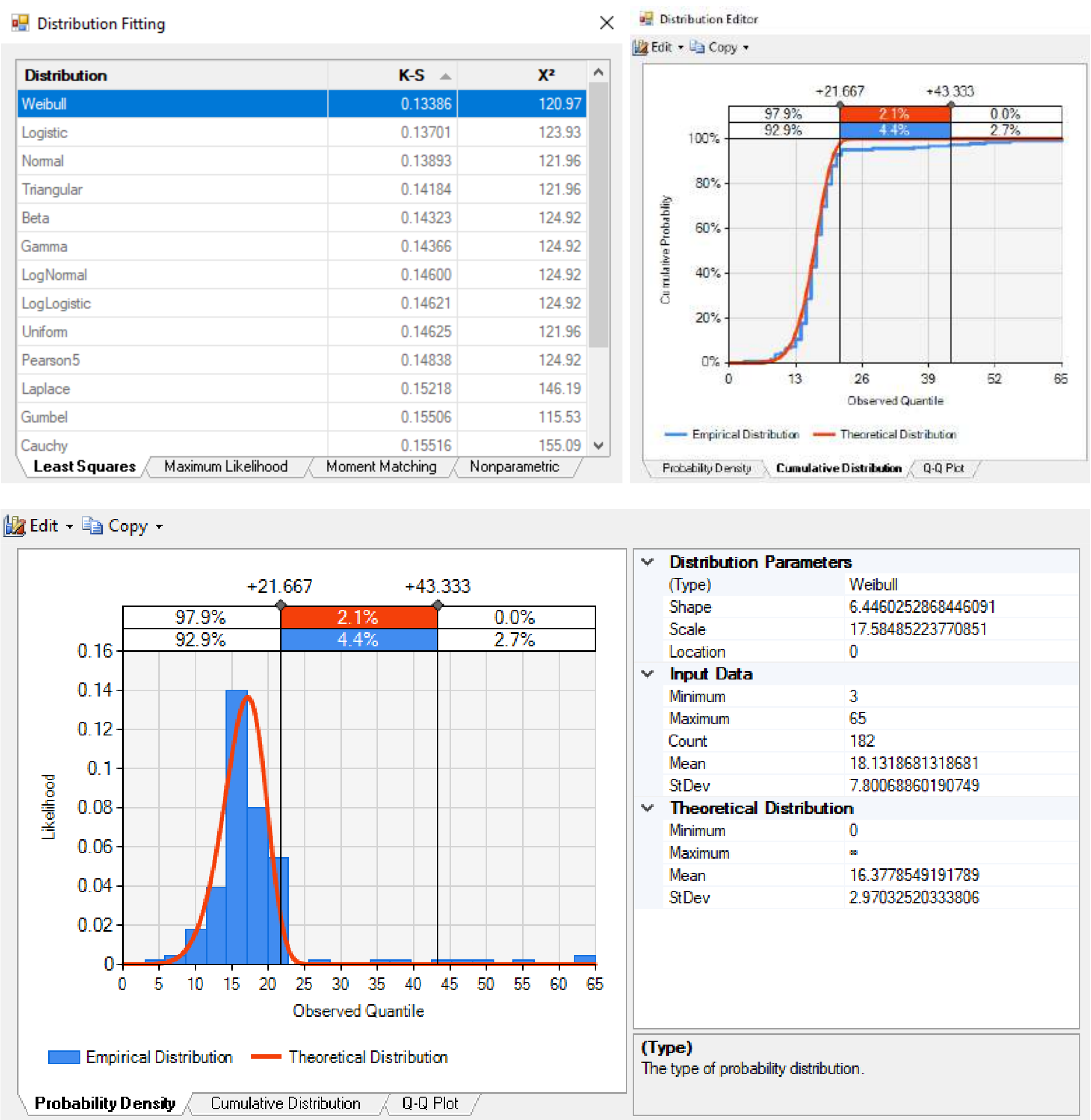


Figure 18: Weibull distribution is fitting for the concrete truck LOADING cycle.

Figure 18, demonstrates the statistical distribution of automatically fitted and the selected result of loading duration (time) for the concrete truck loading task cycle.

Accordingly, for each RMC to site delivery operation task (cycle), sample data were collected and interred into Simphony CYCLONE input data analyzer, and their selected best-fitting output result is summarized in Table 42.

Table 42. Summary of statistical fitting distribution for concrete site delivery operation.

Data analyze cycle		Fit Distribution	Distribution type	Distribution parameters	Input fit result					Goodness-of-fit test		Fitting criteria
					Min.	Max.	Mean	StDv	Count	K-S	X^2	
Truck Loading Time		Least squares	Weibull (Scale, Shape, Location)	Weibull (6.446, 17.584,0)	3	65	18.13	7.8	182	0.134	120.97	Auto Fit
		Maximum likelihood	Cauchy (Location, Scale)	Cauchy (16.933, 1.774)						0.101	110.58	
		Moment matching	Log Logistic (Scale, Location)	Log Logistic (17. 096, 5.592)						0.173	90.14	
Traveling Time	Route A	Least squares	Weibull (Scale, Shape, Location)	Weibull (7.011, 64.665, 0)	43	100	64.05	10.96	36	0.197	10.67	
		Maximum likelihood	Gamma (Scale, Shape)	Gamma (35.469, 1.806)						0.129	12.22	
		Moment matching	Gamma (Scale, Shape)	Gamma (34.130, 1.876)						0.126	12.22	Auto Fit
	Route B	Least squares	Weibull (Scale, Shape, Location)	Weibull (7.731, 85.289, 0)	55	125	84.43	13.28	42	0.171	16.67	
		Maximum likelihood	Log Logistic (Scale, Location)	Log Logistic (83.335, 11.591)						0.116	11.71	Auto Fit
		Moment matching	Pearson5 (Shape, Scale)	Pearson5 (42.379, 3493.595)						0.117	14.00	
	Route C	Least squares	Pareto (Scale, Shape)	Pareto (11.758, 1.432)	6	85	28.37	17.11	104	0.198	108.54	
		Maximum likelihood	Pearson5 (Shape, Scale)	Pearson5 (3.533, 73.331)						0.165	84.31	Auto Fit
		Moment matching	Beta (Alpha, Beta, Low, High)	Beta (0.941, 2.383, 6, 85)						0.178	99.31	
Positioning Time	Site 1	Least squares	Triangular (Low, High, Mode)	Triangular (-5.679, 27.402, -0.881)	1	80	11.63	13.22	104	0.262	158.85	
		Maximum likelihood	Weibull (Scale, Shape, Location)	Weibull (0.959, 11.391, 0)						0.164	117.77	Auto Fit
		Moment matching	Exponential (Mean)	Exponential (11.63)						0.179	145.92	

	Site 2	Least squares	Exponential (Mean)	Exponential (15.01)	1	75	18.06	17.91	78	0.127	28.92	
		Maximum likelihood	Gamma (Scale, Shape)	Gamma (0.949, 19.031)						0.106	23.28	Auto Fit
		Moment matching	Exponential (Mean)	Exponential (18.06)						0.113	23.28	
Dumping Time	Site 1	Least squares	Pearson5 (Shape, Scale)	Pearson5 (1.919, 37.022)	7	152	34.85	27.48	104	0.110	29.15	
		Maximum likelihood	Pearson5 (Shape, Scale)	Pearson5 (2.451, 53.452)						0.088	36.77	Auto Fit
		Moment matching	Gamma (Scale, Shape)	Gamma (1.608, 21.670)						0.133	30.54	
	Site 2	Least squares	Uniform (Low, High)	Uniform (31.224, 162.747)	25	215	100.60	40.89	78	0.069	10.72	
		Maximum likelihood	Weibull (Scale, Shape, Location)	Weibull (2.670, 113.363, 0)						0.058	7.64	Auto Fit
		Moment matching	Weibull (Scale, Shape, Location)	Weibull (2.647, 113.201, 0)						0.059	6.10	
Washing @Site Time	Site 1	Least squares	Chi-Square (Freedom)	Chi-Square (11)	3	24	13.56	3.55	104	0.433	336.08	
		Maximum likelihood	Beta (Alpha, Beta, Low, High)	Beta (3.898, 3.856, 3, 24)						0.260	312.77	
		Moment matching	Triangular (Low, High, Mode)	Triangular (3.647, 24.187, 12.838)						0.253	312.77	Auto Fit
	Site 2	Least squares	Uniform (Low, High)	Uniform (8.825, 20.701)	10	25	17.23	3.39	78	0.456	256.87	
		Maximum likelihood	Gumbel (Location, Scale)	Gumbel (15.543, 3.274)						0.243	218.41	
		Moment matching	Uniform (Low, High)	Uniform (11.347, 23.113)						0.246	219.44	Auto Fit
Returning Time	Route A	Least squares	Uniform (Low, High)	Uniform (32.216, 79.471)	35	100	60.91	16.69	34	0.176	11.29	
		Maximum likelihood	Log Logistic (Scale, Location)	Log Logistic (58.498, 6.406)						0.128	10.47	Auto Fit
		Moment matching	Beta (Alpha, Beta, Low, High)	Beta (1.05, 1.584, 35, 100)						0.129	5.53	

	Route B	Least squares	Uniform (Low, High)	Uniform (43.134, 98.893)	40	120	74.77	17.68	44	0.145	10.18	
		Maximum likelihood	Beta (Alpha, Beta, Low, High)	Beta (1.752, 2.278, 40, 120)						0.101	16.73	Auto Fit
		Moment matching	Beta (Alpha, Beta, Low, High)	Beta (1.752, 2.278, 40, 120)						0.101	16.73	
	Route C	Least squares	Log Logistic (Scale, Location)	Log Logistic (21.219, 2.682)	10	75	26.53	14.02	104	0.122	41.15	
		Maximum likelihood	Beta (Alpha, Beta, Low, High)	Beta (0.781, 2.292, 10, 75)						0.096	40.46	Auto Fit
		Moment matching	Beta (Alpha, Beta, Low, High)	Beta (0.781, 2.292, 10, 75)						0.096	40.46	
Washing @Plant Time	Site 1	Least squares	Uniform (Low, High)	Uniform (23.985, 31.039)	25	31	28.02	2.02	104	0.151	75.31	
		Maximum likelihood	Log Logistic (Scale, Location)	Log Logistic (27.961, 22.640)						0.131	75.31	
		Moment matching	Uniform (Low, High)	Uniform (24.522, 31.516)						0.088	75.31	Auto Fit
	Site 2	Least squares	Uniform (Low, High)	Uniform (24.043, 30.698)	25	31	27.95	1.96	78	0.184	45.59	
		Maximum likelihood	Logistic (Location, Scale)	Logistic (27.904, 1.182)						0.141	45.59	
		Moment matching	Uniform (Low, High)	Uniform (24.553, 31.344)						0.121	45.59	Auto Fit

4.4.3 Run Simulation Model (Simphony CYCLONE).

After proper input data analysis is performed and the best goodness-of-fit statistic distribution is selected for the sample data, the next important step to do is running a simulation model, but before doing the simulation running, checking the simulation modeling process is important, including accreditation, verification, and validation of the simulation models. According to Banks et al. (2014), one of the most challenging issues a simulation analyst has is figuring out whether a simulation model accurately represents the real system under study.

4.4.3.1 Model Accreditation.

Typically, model accreditation is done by a third party who assesses the model's validity, reliability, and how simple it is for the intended user to use. Model accreditation seeks to certify that the simulation model and the supporting documentation meet all modeling standards. (AbouRizk et al. 2015)

4.4.3.2 Simulation model verification.

It is essential to test that a simulation model is functioning properly and accurately simulating the real-world situation as it arises. Verification entails checking the computer model for internal consistency and applying the conceptual model's logic.

The Simphony-CYCLONE simulation software offers a check and tracing option to ensure that the model's input data statistical probability distribution fits a sample of data and that the logical work sequence is situated by actual operational procedures. It also reports any model errors so that the modeler can take appropriate action. When the simulation model is running, it reports if there are any logical and data errors.

Accordingly, the developed model for this research has been checked and traced to the model integrity and goodness-of-fit data carried out using the built-in tool in Simphony CYCLONE.

4.4.3.3 Simulation model validation.

Model validation is typically characterized as evidence that a computerized model within its area of applicability has a range of accuracy that is satisfactory and compatible with the model's intended use, (Sargent 2011).

In this study, the simulation model of the RMC to site delivery operation was validated using face validity by presenting it to the selected concrete batching plant. This was done to see if the conceptual and logical sequence diagram and the model were valid.

Additionally, the RMC-to-site delivery operation model was created using a selection of sample projects. Every cycle, resource, and event was recorded from the actual site operation and then modeled appropriately, which can also demonstrate that the model was created as a replica of a real-world operation.

4.4.4 Simulation model output analysis.

Some researcher confirms that Hillier and Lieberman (2001) states, many long computers run may be needed to obtain good estimates of how well all the alternative designs of the system would perform. AbouRizk et al (2015) state by strengthening the above idea, the larger the number of runs, the more accurate the results. Accordingly in this study, for every run of the simulation experiment, 1000 (One thousand) runs have been performed using the multiple-run feature of Simphony CYCLONE.

In this study, a total of 182 sample data were collected for the overall RMC to site delivery model and entered into simulation software according to Simphony CYCLONE input data analyzer requirement, and the result of the input data analyzer report collected with auto fit distribution and goodness-of-fit. After developing proper input data, the next step is developing additional input data, for the analysis of the RMC to site delivery simulation model. Always for the simulation to be run it needs an initial entity, for this study, the initial entity was the quantity of concrete that has to be delivered to sites in terms of truckload, and this initial entity is an optimal concrete output result of EOQ-based ANN predictive model, which it was 1307.33 m^3 of concrete. This integration of the Simphony CYCLONE model with the ANN predictive model was one of the objectives of this research. And makes the Simphony CYCLONE model developed based on the true predictive value of concrete rather than making assumptions on it, most simulation models are developed based on assumption values but this research tries to avoid such assumptions and predict the real-world operation.

Table 43. Input data summary for the overall RMC-to-site delivery model.

Delivery Cycle		**Input Data**					**Distribution Fitting**		
		Count	Min.	Max.	Mean	StDv	Distribution	Parameter	Best Fit
Loading Cycle		182	3	65	18.13	7.8	Least squares	Weibull	Auto Fit (K-S/X^2)
Traveling Cycle	Route A	36	43	100	64.05	10.96	Moment matching	Gamma	Auto Fit (K-S/X^2)
	Route B	42	55	125	84.43	13.28	Maximum likelihood	Log Logistic	Auto Fit (K-S/X^2)
	Route C	104	6	85	28.37	17.11	Maximum likelihood	Pearson5	Auto Fit (K-S/X^2)
Positioning Cycle	Site 1	104	1	80	11.63	13.22	Maximum likelihood	Weibull	Auto Fit (K-S/X^2)
	Site 2	78	1	75	18.06	17.91	Maximum likelihood	Gamma	Auto Fit (K-S/X^2)
Dumping Cycle	Site 1	104	7	152	34.85	27.48	Maximum likelihood	Pearson5	Auto Fit (K-S/X^2)
	Site 2	78	25	215	100.60	40.89	Maximum likelihood	Weibull	Auto Fit (K-S/X^2)
Washing @Site Cycle	Site 1	104	3	24	13.56	3.55	Moment matching	Triangular	Auto Fit (K-S/X^2)
	Site 2	78	10	25	17.23	3.39	Moment matching	Uniform	Auto Fit (K-S/X^2)
Returning Cycle	Route A	34	35	100	60.91	16.69	Maximum likelihood	Log Logistic	Auto Fit (K-S/X^2)
	Route B	44	40	120	74.77	17.68	Maximum likelihood	Beta	Auto Fit (K-S/X^2)
	Route C	104	10	75	26.53	14.02	Maximum likelihood	Beta	Auto Fit (K-S/X^2)
Washing @Plant Cycle	Site 1	104	25	31	28.02	2.02	Moment matching	Uniform	Auto Fit (K-S/X^2)
	Site 2	78	25	31	27.95	1.96	Moment matching	Uniform	Auto Fit (K-S/X^2)

Amount of concrete		Delivered Concrete Quantity (cum)			Resource (in number)		Event Seen in The Cycle	
Truckload	m^3	Min.	Max.	Avg.	Truck	Mixer	Number	Note
184	1307.33	3	9.5	7.16	1-10	2	8	Cement Gate Problem

The statistical report generates while considering the characteristics of the RMC site delivery operations, indicates that it is possible to estimate the total simulation time to finish an operation, equipment/resource production rate, average waiting times, truck interarrival time, number of trucks, and production rates of the system. Figure 19 discusses those points in detail.

Statistics Report

Date: 2022-12-24

Project: Model

Scenario: Scenario1

Run: All Runs (of 1000)

Note: When summarized across all runs, the mean value reported for a statistic is the mean of the means of each run; the minimum value reported is the minimum of the means of each run; the maximum value reported is the maximum of the means of each run; and so forth.

Non-Intrinsic Statistics

Element Name	Mean Value	Standard Deviation	Observation Count	Minimum Value	Maximum Value
Scenario1 (Termination Time)	8,452.815	730.297	1,000.000	6,600.835	14,858.231

Intrinsic Statistics

Element Name	Mean Value	Standard Deviation	Minimum Value	Maximum Value	Current Value
Amount of Concrete (184 TL) (PercentNonempty)	0.938	0.017	0.883	0.979	0.920
Available Truck (PercentNonempty)	0.063	0.017	0.023	0.119	0.075
Mixer (PercentNonempty)	0.963	0.007	0.940	0.981	0.956
Placing Crew (PercentNonempty)	0.536	0.078	0.260	0.718	0.545
Placing Crew2 (PercentNonempty)	0.059	0.039	0.017	0.494	0.083
Waiting to Dump (PercentNonempty)	0.188	0.078	0.042	0.616	0.147
Waiting to Dump2 (PercentNonempty)	0.845	0.076	0.431	0.971	0.830
Waiting to Wash Truck @Plant (PercentNonempty)	0.066	0.024	0.011	0.194	0.081
Waiting to Wash Truck @Plant2 (PercentNonempty)	0.007	0.004	0.000	0.028	0.013
Washing Crew (PercentNonempty)	0.647	0.048	0.465	0.795	0.571
Washing Crew2 (PercentNonempty)	0.739	0.015	0.702	0.861	0.723

Counters

Element Name	Final Count	Production Rate	Average Interarrival	First Arrival	Last Arrival
Crew Production	105.263	0.017	76.632	90.681	8,017.476
Crew Production2	78.737	0.009	104.660	212.949	8,334.450
Mixer Production	184.000	0.032	43.338	14.715	7,945.577
Overall Truck Production	184.000	0.025	45.357	152.541	8,452.815
Returning Counter	105.263	0.016	76.653	129.304	8,058.326
Returning Counter2	78.737	0.009	104.675	296.537	8,419.131

Traveling Counter	105.263	0.017	76.398	42.052	7,944.172
Traveling Counter2	78.737	0.012	101.390	96.259	7,962.830
Truck Production After Dumping	105.263	0.017	76.632	90.681	8,017.476
Truck Production After Dumping2	78.737	0.009	104.660	212.949	8,334.450
Washing Counter	105.263	0.016	76.706	157.380	8,091.892
Washing Counter2	78.737	0.009	104.687	324.496	8,447.991
Washing Crew Counter	105.263	0.016	76.706	157.380	8,091.892
Washing Crew Counter2	78.737	0.009	104.687	324.496	8,447.991

Waiting Files

Element Name	Average Length	Standard Deviation	Maximum Length	Current Length	Average Wait Time
Amount of Concrete (184 TL)	83.828	4.287	116.532	82.737	3,851.141
Available Truck	0.282	0.076	0.563	0.326	1.068
Mixer	1.641	0.030	1.796	1.599	69.749
Placing Crew	0.536	0.078	0.718	0.545	39.809
Placing Crew2	0.059	0.039	0.494	0.083	5.037
Waiting to Dump	0.332	0.259	3.503	0.206	26.604
Waiting to Dump2	2.262	0.397	3.360	1.901	242.742
Waiting to Wash Truck @Plant	0.073	0.030	0.240	0.092	5.664
Waiting to Wash Truck @Plant2	0.007	0.004	0.028	0.013	0.786
Washing Crew	0.647	0.048	0.795	0.571	49.468
Washing Crew2	0.739	0.015	0.861	0.723	79.563

Figure 19: Statistics report of Simphony CYCLONE Simulation for the overall model.

4.4.4.1. Overall model result comparison and discussion.

This section presents the discussion and results from a comparison of the overall model based on the assigned number of trucks, minimum inter-arrival time, and optimum production rate of the system. Table 44 and Figure 20 show the summary of the simulation result of the overall concrete site delivery model.

Table 44. Overall concrete site delivery simulation model statistics report /summary/.

Overall Delivery Summary Report (184 TL)										
No of Truck	Production Rate				Idleness (Waiting)				Truck Cycle Time (Inter Arrival)	Termination Time (Mean)
	Truck		Mixer Plant		Truck		Mixer Plant			
	TL/min.	TP/m³/hr.	TL/min.	MP/m³/hr.	Avg. Waiting Time. (min.)	TI %age	Avg. Waiting Time. (min.)	MI %age		
1	0.004	1.72	0.005	2.15	0.000	0.00%	440.00	100%	228.25	42,346.43
2	0.009	3.87	0.010	4.29	0.000	0.60%	218.53	99.7%	118.72	21,912.71
3	0.011	4.73	0.013	5.58	0.080	1.40%	145.48	99.2%	82.09	15,191.33
4	0.015	6.44	0.018	7.73	0.177	2.20%	110.87	98.5%	64.88	12,033.50
5	0.018	7.73	0.023	9.88	0.344	3.10%	91.30	97.8%	55.20	10,258.32
6	0.019	8.16	0.025	10.74	0.533	4.00%	79.86	97.1%	49.70	9,248.57
7	0.021	9.02	0.027	11.60	0.789	5.10%	73.39	96.6%	46.73	8,705.17
8	0.025	10.74	0.032	13.75	1.068	6.30%	69.75	96.3%	45.36	8,452.82
9	0.022	9.45	0.031	13.32	1.401	7.60%	67.17	96.1%	44.56	8,305.34
10	0.021	9.02	0.029	12.46	1.778	8.80%	65.45	95.8%	41.16	8,232.94
Legend	TP=Truck Prod. Rate		MP=Mixer Prod. Rate		TI=Truck Idleness		MI=Mixer Idleness		TL=Truck Load	

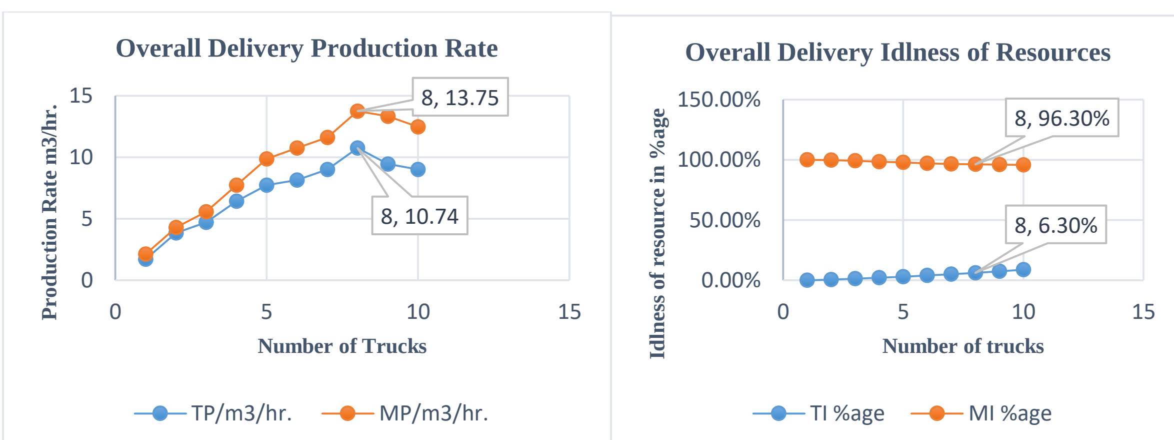


Figure 20: Overall concrete site delivery model statistics report /Chart form/.

Table 44 and Figure 20 is confirming that a higher production rate of the system has been recorded on the assigned truck number 8, a detailed discussion is presented here below:

- Assigning 8 trucks: is resulting, the total time that it took to complete the simulation was 8452.815min or 140.88 hours. The production rate of the overall system was 0.025TL/min (Truck Load) or 10.74 m^3/hr. at the same time, the production rate of the mixer plant at this point is 0.032TL/min (Truck Load) or 13.75 m^3/hr. Interarrival of the truck takes 45.36 minutes for 8 trucks. With regards to resource idleness in the model, trucks waited approximately 6.3% of the time, mixer plant waited approximately 96.3% of the time.

V. CHAPTER FIVE - RESEARCH CONCLUSION AND RECOMMENDATION

5.1 Conclusion

Based on the analysis done in the previous chapter, this section provides a summary of the study's findings. The following are the study's findings:

5.1.1 Review of objective one

The main aim is to develop an EOQ-based ANN predictive model for the prediction of the optimal order quantity and reordering point of RMC raw materials.

Based on this an EOQ model for the raw materials of RMC (aggregate, sand, and cement) was performed. And check their predictive using Artificial Neural Network (ANN) toolbox of the WEKA 3.8.6 for the testing set. The testing predictive analysis results confirmed that the ANN predictive had higher accuracy in the prediction of the optimal order quantity and reordering point of raw materials with an accuracy measurements value of ((0.98 correlation coefficient and 0.2935 MAE and 0.9998 correlation coefficient and 0.2935 MAE for EOQ and ROP of Aggregate), (0.9831 correlation coefficient and 0.418 MAE and 0.9999 correlation coefficient and 0.1673 MAE for EOQ and ROP of Sand), and (0.9951 correlation coefficient and 1.6512 MAE and 0.9828 correlation coefficient and 6.1731 MAE for EOQ and ROP of Cement)).

And their optimal testing ANN predictive output results for EOQ and ROP of raw materials are (37.731 m^3 and 27.184 m^3 for EOQ and ROP of Aggregate respectively), (37.651 m^3 and 33.642 m^3 for EOQ and ROP of Sand respectively), and (221.817 m^3 and 222.507 m^3 for EOQ and ROP of Cement respectively).

5.1.2 Review of objective two

The main aim is to estimate the optimal number and volume of raw materials reservoirs required for the RMC batching plant using the ANN predictive model output.

Based on this an EOQ-based ANN predictive analysis was performed for each raw material (Aggregate, Sand, and Cement) using this predictive output results the raw materials reservoirs' optimal number and volume are minimized, and the calculated percentage results for the reduction of reservoirs are:

There was a 63.35%, 76.47%, and 11.27% reduction in the estimation of the optimal size of the required reservoirs for Aggregate, Sand, and Cement.

5.1.3 Review of objective three.

The main aim is to develop and optimize an effective RMC-to-site delivery simulation model by integrating it with the output of EOQ-based ANN predictive optimal ordered quantity.

Based on this, observed collected data of 182 (one hundred eighty-two) were collected with different task situations to represent the real-world situation, and EOQ-based ANN predictive analysis maximum output results were used to get the maximum delivered amount of concrete used for the analysis of DES. The predictive output result was 1307.33 m^3.

Finally, we get an overall simulation output result, which is maximum by assigning 8 number of truck, with an overall production rate of 0.025 TL/min (10.74m^3/hr.) and 0.032 TL/min. (13.75 m^3/hr.) respectively for the truck and mixer.

5.2 Recommendation

Construction industry deal with complex facilities that are generally composed of multiple components, and involve multiple stakeholders, many supply chains, and a multitude of engineers and professionals. However, to deliver a good quality product in a well-executed manner, planners need to be able to develop models with advancements in computer software. ANN and Simulation is one of the powerful techniques for supporting the decision-making process in construction management.

5.3 Recommendation for Further Research

This research focused on the development and integration of EOQ, ANN, and DES for the RMC batching plant to have an optimized inventory control system, and an effective concrete site delivery planning technique using simulation software.

This research recommends the following for further research and investigation:

1. Conduct the same research by only integrating concrete production optimization models for RMC production with this research, like linear programming, since this study covers the raw materials inventory control and delivery of RMC to sites.

2. Conduct additional research to improve the models that have been developed and the data collecting format by adding specific events and production unit costs to each resource that has been assigned to the model.

REFERENCES

Abebe Dinku, (2005). "The Need for Standardization of Aggregates for Concrete Production in Ethiopian Construction Industry." International Conference on African Development, Center for African Development Policy Research, Western Michigan University.

AbouRizk S. M. (2010), "Role of Simulation in Construction Engineering and Management", Journal of Construction Engineering and Management © Asce / October 2010 / 1140-1153.

AbouRizk S. M. and Hague S. (2009) "An Overview of the COSYE Environment for Construction Simulation" Proceedings of the 2009 Winter Simulation Conference M. D. Rossetti, R. R. Hill, B. Johansson, A. Dunkin and R. G. Ingalls, eds. 2624-2634.

AbouRizk S. M. and Mohamed Y. (2000), "Simphony- An Integrated Environment for Construction Simulation" Proceedings of the 2000 Winter Simulation Conference, J.A. Joines, R. R. Barton, K. Kang, and P. A. Fishwick, eds. 1907-1914.

AbouRizk S. M., Hague S. A., and Ekyalimpa R. (2015). "Introduction to Simulation," "Construction Simulation an Introduction Using Simphony" Hole School of Construction Engineering, Department of Civil and Environmental Engineering, University of Alberta, and First Edition: October 2015.

AbouRizk, S. M., Hague, A. S., & Ekylimpa, R. (2016). Construction simulation: An introduction using SiMPHONY (First ed.). Edmonton, Canada: Hole School of Construction Engineering, Department of Civil and Environmental Engineering, University of Alberta.

Akkol, S. (2015). Comparison of Artificial Neural Network and Multiple Linear Regression for Prediction of Live Weight in Hair Goats, Conference 8th of The Eastern Mediterranean Region of the International Biometric Society, Turkey, 27(1) 21-29

Alemayehu, S. (2014). Testing regression models to estimate costs of road construction projects. Addis Ababa Institute of Technology University, School of Civil and Environmental Engineering. Addis Ababa University. Retrieved from http://localhost/xmlui/handle/123456789/6252.

Almusawi, H. T., & Burhan, A. M. (2020). Evaluation of the Productivity of Ready Mixed Concrete Batch Plant Using Artificial Intelligence Techniques. IOP Conference Series. https://doi.org/10.1088/1757-899x/901/1/012020.

Arnaud, K. (2019). A factor model to predict the construction labor productivity in building projects. Addis Ababa Institute of Technology University, School of Civil and Environmental Engineering. Addis Ababa University. Retrieved from http://localhost/xmlui/handle/123456789/18398.

ASTM (1999). Annual books of ASTM standards.

Azambuja, M.; Chen, X. (2014). Risk Assessment of a Ready-Mix Concrete Supply Chain. Construction Research Congress, ASCE, p. 1695-1703.

Banks J., Carson J.S., Nelson B. L. and Nicol D.M. (2001), "Discrete-Event System Simulation" Fourth Edition, Prentice Hall International Series Industrial and System Engineering, W.J. Fabrycky and J.H. Mize, Series Editor, Upper Saddle River, NJ, 2001.

Biruk S. (2015). "Dispatching concrete trucks using simulation method", Budownictwo i Architektura 14(2) (2015) 5-10.

Chao, L.C.; Skibniewski, M.J. (1995). Neural-Network Method of Estimating Construction Techn ology Acceptability. J. Constr. Eng. Manag.-ASCE.

Chua, S. D., & Li, M. G. (2002). RISim: Resource-interacted simulation modeling in construction. Journal of Construction Engineering and Management, 128(3), 95-202. doi:10.1061/(ASCE)0733-9364(2002)128:3(195).

Deb, D., Dey. R., and Balas. V. E.(2019).Engineering Research Methodology. A Practical Insight for Researchers. Springer Nature Singapore Pte Ltd,vol. 153.

Dewar, J. (1992). Manual of Ready-Mixed-Concrete. London: British Ready Mixed Concrete Association.

Duggal S.K. (2000). Building Materials (3rd Edition), New age international publishers.

Easy Mix Concrete (2021).The Ready Mix Concrete Process. Easy Mix Concrete UK Ltd. Retrieved May 23, 2022, from https://www.easymixconcrete.com/news/the-ready-mix-concrete-process.

Ethiopian standard. (2005) Mixing water for concrete ES 2310:2005

Feng C. W. and Wu H. T., (2006). "Integrating fmGA and CYCLONE to optimize the schedule of dispatching RMC trucks" Automation in Construction 15 (2006) 186 – 199.

Gagg, Colin R. (2014). "Cement and concrete as an engineering material: An historic appraisal and case study analysis". Engineering Failure Analysis. 40: 114-140. doi:10.1016/j.engfailanal.2014.02.004. ISSN 1350-6307.

Gambhir, M. (2002). Concrete Technology, 2nd Edition. MC Grawhill Book.

Ganeshan, R., and Harrison, T.P. (2002). "An introduction to Supply Chain Management." Department of Management. Science and Information Systems, Penn State University. US.

Gaynor, R. D. (1978). Ready-Mixed Concrete. In Significance of Tests and Properties of Concrete and Concrete Making Materials. ASTM International.

George Earl Troxell, Harmer Davis & Joe W.Kelly. (1965). Composition and properties of concrete. s.l. : MC Graw Hill Book Company.

Getachew, B. (2016). Role of building information modeling in improving building design process. Addis Ababa Institute of Technology University, School of Civil and Environmental engineering. Addis Ababa University. Retrieved from http://localhost/xmlui/handle/123456789/15090.

Gillis, A. S. (2022). *data splitting*. Enterprise AI. https://www.techtarget.com/searchenterpriseai/definition/data-splitting

Hajjar, D., & AbouRizk, S. M. (1997). AP2-EARTH: A simulation-based system for the estimating and planning of earthing-moving operations. Proceedings of the 1997 Winter Simulation Conference ed. S. Andradbttir, K. J. Healy, D. H. Withers, and B. L. Nelson, (pp. 1103-1110).

Hajjar, D., & AbouRizk, S. M. (1998). Modeling and analysis of aggregate production operation. Journal of Construction Engineering and Management, 124(5), 390-401.

Hajjar, D., & AbouRizk, S. M. (1999). SIMPHONY: An environment for building special-purpose construction simulation tools. Proceedings of the 1999 Winter Simulation Conference, (pp. 998- 1006).

Hajjar, D., & AbouRizk, S. M. (2000). Application framework for development of simulation tools. Journal of Construction Engineering and Management, 14(3), 160-167.

Halpin, D. W., and Riggs, L. S. (1992). Planning and Analysis of Construction Operations, Wiley, New York.

Halpin, D.W. (1977). "CYCLONE - A Method for Modeling Job Site Processes." J. Constr. Div., ASCE, 103(3), 489-499.

Halpin, D.W. and Riggs, L. S. (1992). "Planning and Analysis of Construction Operations." John Wiley & Sons, Inc., New York, N.W.

Hillier, Frederick S., and Gerald J.Lieberman. (1995). Introduction to Operations Research. United States of America: McGraw-Hill, Inc.

Ioannou, G. P. (1990). UM-CYCLONE: Discrete event simulation System user's guide. University of Michigan, Civil and Environmental Engineering. Ann Arbor, Michigan: Center for Construction and Management.

Ioannou, G. P., & Martinez, J. C. (1996). Simulation of the complex construction process. Proceedings of the 1996 Winter Simulation Conference (pp. 1321-1328). Coronado, California, USA: IEEE. doi:https://doi.org/10.1109/WSC.1996.873442.

Jabri, A. (2014). Agent-Based Modeling and simulation of earthmoving operations. MSc Thesis, Concordia University, Building, Civil and Environmental Engineering, Montreal, Quebec, Canada.

Jang H. et al. (2003). "A project manager's level of satisfaction in construction logistics" Can. J. Civ. Eng. 30: 1133–1142.

Jason Portas, Simaan AbouRizk. (1997). Neural network model for estimating construction productivity Journal of Construction Engineering and Management, Vol. 123, No.4, December, 1997. ©ASCE, ISSN 0733-9364/97/0004-0399- 04101. Paper No. 14120.

Kassahun A. (2017). Growth Potential and Challenges of Ready-Mix Concrete Marketthe Addis Scenario. Icapitalafrica.Org.

Kassahun, R. (2018). Cash flow forecasting using Monte Carlo Simulation for building construction projects. Addis Ababa Institute of Technology University, School of Civil and Environmental Engineering. Research Gate. Retrieved from https://www.researchgate.net/publication/327339022.

Keah Choon Tan. (2001). "A framework of supply chain management literature". European Journal of Purchasing & Supply Management 7 (2001) 39 – 48.

Ketema, E. (2019). Tower crane location optimization for high rise buildings in the financial district of Addis Ababa. Addis Ababa Institute of Technology University, School of Civil and Environmental Engineering. Addis Ababa University. Retrieved from http://localhost/xmlui/handle/123456789/19547.

Kononenko, I, & Kukar, M. (2007). Machine Learning and Data Mining: Introduction to Principles and Algorithms. Horwood publishing limited, Chapter 1, pp. 1–36.

Kothari, C.R. (2004). Research methodology, Methods and Techniques. New Age International Limited Publishers.

Kozniewski E., and Orlowski Z. (2003). "Concrete Mix Transportation Modelling" Journal of Civil Engineering and Management, Vol IX No I, 52-58.

Kriesel, D. (2005). A Brief Introduction to Neural Networks, Germany, University of Bonn.

Kumar, Ranjit (1999). Research Methodology: A step-by-step approach. London: Sage Publications.

L1Supply (Ed.). (2018). Ready Mix Concrete (RMC). What are the different types of Ready Mix Concrete (RMC) used in the construction industry? Retrieved April 20, 2022, from https://l1supply.com/blog/types-of-ready-mix-concrete#

Lee, D., Yi, C., Lim, T., & Arditi, D. (2010). Integrated simulation system for construction operation and project schedule. Journal of Computing in Civil Engineering, 24(6), 557-569.

Li-Chung Chao, Miroslaw J. Skibniewsk. (1995). Neural network method of estimating construction technology acceptability Journal of Construction Engineering and Management, Vol. 121, No.1, March, 1995. ©ASCE, ISSN 0733-9364/95/0001- 0130-0142Paper No. 6826.

Lu, M., Anson, M., Tang, L. S., & Ying, C. Y. (2003). HKCONSIM: A practical simulation solution to planning concrete plant operations in Hong Kong. Journal of Construction Engineering and Management, 129(5), 547-554. doi:10.1061/(ASCE) 0733-9364(2003)129:5(547).

Mahajan,R. and Buthello R. (2015). Quality Control of Ready Mixed Concrete. IOSR Journal of Mechanical and Civil Engineering, 12(15).

Markus K., Ilka H. and Sven S. (2011), "On-Site Logistics Simulation in Early Planning Phases", CONVR201 International Conference on Construction Applications of Virtual Reality.

Martin Christopher. (1992). "Logistic and Supply Chain Management".

Martinez, J. C. (1996). STROBOSCOPE: State and resource-based simulation of construction process. Ph.D. Thesis, University of Michigan, Civil Engineering.

Martinez, J. C., & Ioannou, G. P. (1994). GENERAL purpose simulation with STROBOSCOPE. 1994 Winter Simulation Conference (pp. 1159-1166). Lake Buena Vista, FL, USA: IEEE. doi:https://doi.org/10.1109/WSC.1994.717503.

Martinez, J. C., & Ioannou, G. P. (1995). Advantages of the Activity Scanning Approach in the Modeling of Complex Construction Processes. Proceedings of the 1995 Winter Simulation Conference (pp. 1024-1031). IEEE. doi:https://doi.org/10.1145/224401.224767.

Martinez, J. C., & Ioannou, G. P. (1997). State-based probabilistic scheduling using STROBOSCOPE's CPM Add-On. Proceedings, Construction Congress V (pp. 438-445). Minneapolis, MN: ASCE.

Martinez, J. C., Ioannou, G. P., & Carr, R. (1994). State and resource-based construction process simulation. 177-184.

Marzouk M. and Younes A. (2013), "A Simulation Based Decision Tool for Transportation of Ready Mixed Concrete", International Journal of Architecture, Engineering and Construction, Vol 2, No.4, 234-245.

Marzouk, M., & Moselhi, O. (2003). Object-oriented simulation model for earthmoving operations. Journal of Construction Engineering and Management, 129(2), 173-181. doi:10.1061/(ASCE)0733-9364(2003)129:2(173).

Matheas, B. (2009). Analysis, design, and cost-effectiveness of the precast beam-slab system. Addis Ababa Institute of Technology University, School of Civil and Environmental Engineering. Addis Ababa University. Retrieved from http://localhost/xmlui/handle/123456789/1578.

Mengistu A. (2010). Investigation of Calcite and Volcanic Ash for Their Utilizations as Cement Filling and Additive Materials, Addis Ababa University Master's thesis.

Mikyas, A. (1987). Construction Materials Text Book. Addis Ababa University.

Minh- Tu Cao; Min-Yuan Cheng; Yu-Wei Wu. (2015). Hybrid Computational Model for Forecasting Taiwan Construction Cost Index 10.1061/ (ASCE) CO.1943-7862 .0000948.American Society of Civil Engineers.

Mohamed Marzouk, Ahmed Amin. (2013). Predicting Construction Materials Prices Using Fuzzy Logic and Neural Networks 10.1061(ASCE) CO.1943-7862.0000707. American Society of Civil Engineers.

Mohamed, Y., & AbouRizk, M. S. (2006). A hybrid approach for developing special-purpose simulation tools. Canadian Journal of Civil Engineering, 33, 1505-1515. doi:10.1139/L06-073.

Murdook, L.J and Brook, K.M. (1979). Concrete Materials and Practice (5th edition);, published by Edward Thold

Nellihela, P. (2022). What is K-fold Cross Validation? - Towards Data Science. Medium. https://towardsdatascience.com/what-is-k-fold-cross-validation-5a7bb241d82f

Neville A.M. and Brooks J.J. (2010). Concrete technology (second Edition), Pearson Education Limited.

Neville, A. (2011). Properties of Concrete, 5th Edition.

O"Brien, W. J., Formoso, C. T., Vrijhoef, R., and London, K. A. (2009). Construction Supply Chain Management Handbook, CRC Press/Taylor and Francis, Boca Raton & London.

Omar, B. (2016). The Importance of Supply Chain Management for Ready Mixed Concrete Production and Delivery Process. UTM Engineering - University Technology Malaysia.

Park, M. and Lee S. (2011). Supply chain management model for ready mixed concrete Automation in Construction, 20(1), 44-55. Pearson Education, Inc.

Patel, D.A.; Jha, K.N. (2015). Neural Network Model for the Prediction of Safe Work Behavior i n Construction Projects. J. Constr. Eng. Manag.

Poh, C.Q.X., Ubeynarayana, C.U., & Goh, Y.M. (2018). Safety Leading Indicators for Construction Sites: A Machine Learning Approach, Automation in Construction, Vol. 93, pp. 375-386.

Purdue University. (2020). Simulation in Construction Using CYCLONE and MicroCYCLONE. (D. o. Management, Producer, & Purdue University) Retrieved 03 05, 2022, from https://engineering.purdue.edu/CEM/people/Personal/Halpin/Sim/CYCLONE.

Pushkar, A., Senthilvel, M., & Varghese, K. (2018). Automated progress monitoring of masonry activity using photogrammetric point cloud. 35th ISARC.

Ready Mixed Concrete Statistics (2013). European Ready Mixed Concrete Organization.

Rifat Sonmez, James E. Rowings. (1998). Construction labor productivity modeling with neural networks‖. Journal of Construction Engineering and Management, Vol. 124, No. 6, *November December, 1998. ©ASCE, ISSN 0733- 9634/98/0006-04980504. Paper No. 17057.*

Riley, M.J., and D.R. Towill. (2001). Business systems engineering, can it work in construction? New Civil Eng'g. Int., Institute of Civil Engineers.

Ruwanpura J. Y., AbouRizk S. M. (2000). and Fernando S. "Experiences in Implementing Special Purpose Simulation Tool for Utility Tunnel Construction Operations", Tunneling Association of Canada Annual Publication.181-191.

Saad, M., Jones, M., and James, P. (2002). "A review of progress towards the adoption of supply chain management (SCM) relationships in construction." European Journal of Purchasing& Supply Management, 8, 173-183.

Sales@techsciresearch.com, "TechScresearch," (2021). [Online]. Available: https://www.techsciresearch.com/report/india-ready-mixed-concrete-market/4111.html.

Sargent R. G., (2011). "Verification and Validation of Simulation Models" Proceedings of the 2011 Winter Simulation Conference, S. Jain, R.R. Creasey, J. Himmelspach, K.P. White, and M. Fu, eds. 183-198.

Sen, Amiyangshu B. and Shouvik K. (2016). Study on Ready Mix Concrete. International Journal of Scientific and Engineering Research, 1.

Shi, J. (1999). Activity-based construction (ABC) modeling and simulation method. Journal of Construction Engineering and Management, 125(5), 354–360.

Siadat, J., & Ruwanpura, Y. R. (2013). Effective simulation of earth-moving projects. Proceedings of the 2013 Winter Simulation Conference R. Pasupathy, S.-H. Kim, A. Tolk, R. Hill, and M. E. Kuhl, eds (pp. 3282-3293). IEEE.

Sileshi, A. (2018). Planning ready-mix concrete site delivery in Addis Ababa. MSc. Thesis, Addis Ababa Science and Technology University, College of Architecture and Civil Engineering.

Singh, A. (2021). Significance of Research Process in Research Work. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3815032

Smith, S. (1998). Modeling and experimentation of the concrete supply and delivery process. Civil Engineering and Environmental Systems, vol. 16, p. 93–114.

Steven H. et al. (2003). Design and Control of Concrete Mixtures (14th edition) published by Portland Cement Association, Skokie, Illinois, USA.

Sydney Mindess, Francis J.Young and Darwin David (2003). Concrete (2nd Edition),

Tae-Kyung Lim; Sang-Min Park; Hong-Chul Lee; and DongEun Lee. (2016). Artificial Neural Network–Based Slip-Trip Classifier Using Smart Sensor for Construction Workplace 10.1061/ (ASCE) CO.1943-7862.0001049.American Society of Civil Engineers.

Takeyama. M. (1996). Present technology of ready mixed concrete and future prospects. Magazine of concrete Research. Vol. 48 no. 176 pp. 199-209

Taye, G. (2019). Simulation modeling of cost overrun in the construction project in Ethiopia. International Journal of Recent Technology and Engineering (IJRTE), 8(4). doi:DOI:10.35940/ijrte.D9121.118419.

Tommelein, D. I., Carr, I. R., & Odeh, M. A. (1994). Assembly of simulation network using designs, plans, and methods. Journal of Construction Engineering and Management, 120(4), 796-815.

Troxel, G. E. (1956). Composition and Properties of Concrete.

Vrijhoef, R., and Koskela, L. (2000). "The four roles of supply chain management in construction." European journal of purchasing &s supply management, 6, 169-178.

Wang S. Q., Teo C. L. And Ofori G., (2001), "Scheduling the Truck Mixer Arrival for a Ready Mixed Concrete Pour via Simulation with @Risk" Journal of construction research (2001)2,61-71.

Waters, D. (1992). Inventory Control and Management (1st ed.). Wiley.

Winston, W. (2003). "Simulation", "Operation Research Application and Algorithms", Fourth Edition.

Yemane, G. (2020). Analysis of earth moving operation using discrete event simulation. MSc.Thesis, Addis Ababa Institute of Technology University, School of Civil and Environmental Engineering.

Yi-Cheng Liu, Cheng Yeh. (2016). Building Valuation Model of Enterprise Values for Construction Enterprise with Quantile Neural Networks10.1061/(ASCE)CO.1943-7862.0001060.American Society of Civil Engineers.

Yogesh, T. (2016). A Literature Review on Ready-Mixed Concrete Industry in India. International Research Journal of Multidisciplinary Studies, 1.

You, Z.; Wu, C. (2019). A framework for data-driven informatization of the construction compan y. Adv. Eng. Inform. 39, 269–277.

Yx, A.; Ying, Z.B.; Psc, D.; Ld, B. (2021). Machine learning in construction: From shallow to de ep learning. Dev. Built Environ.

Zahran, H., and Nassar, K. (2013). Modeling pipeline projects using computer simulation. Proceedings of the 2013 Winter Simulation Conference (pp. 3269-3281). IEEE. doi:10.1109/WSC.2013.6721692.

Zayed T. M. and Halpin D. W. (2001). "Simulation of Concrete Batch Plant Production", "journal of construction engineering and management" march/april 2001, 127(2): 132-141.

Zewdu and Aregaw. (2015), Causes of Contractor Cost Overrun in Construction Projects : The Case of Ethiopian Construction Sector. Res., vol. 4,(no.4), 180– 191.

ANNEXES

Annex-A: - Observation Data Collection Format

Post Graduate in Construction Technology and Management

Developing a Model for Minimizing Material Inventory and Dispatching of Ready Mixed Concrete to Sites in Addis Ababa

Observed Data Collection Entry Form

Route A (Batching plant - Airport Cargo - Megenagna - Kebena Afncho ber - Yohannes - Pastor - Winget - Asco - Sansusi)

Route B (Batching Plant - Airport Cargo - Yoseph (Mamo) - Gotera Sarbet - Mechare - Torhailoch - Winget - Asco- Sansusi)

Batching Plant and Project Information

Batching Plant			**Project**	
Name			**Name**	
Location			**Location**	
	Project Client	**Project Consultant**	**Project Contractor**	
Date			**Driver Name**	

I. General Information

A. Concrete Truck Type		**B. Truck Plate Number**	
Dump Truck	☐		☐
C. Concrete Mix Design Type		**D. Truck Capacity**	
C-15 ☐	C-25 ☐	9.5 cum	☐
C-20 ☐	C-30 ☐	Other	☐
D. Data Collecting Time		**E. Concrete Placing Crew**	
Road Traffic Jam Hour	☐	Average in Number	☐
Road Traffic Free Hour	☐	**F. Casting Structure**	

Route C have only one route (Bole Homes - Gumruk)

II. Truck Dispatching Full Cycle Observed Entry Data

A. Plant Queuing

Starting T.	
Ending T.	
Quene No	

B. Truck Loading

Starting T.	
Ending T.	

C. Truck Traveling

Starting T.	
Ending T.	
Odometer S	
Odometer F	
Route	

D. Site Queuing

Starting T.	
Ending T.	
Quene No	

F. Washing (Plant)

Starting T.	
Ending T.	

F. Truck Returning

Starting T.	
Ending T.	
Odometer S	
Odometer F	
Route	

F. Washing (Site)

Starting T.	
Ending T.	

E.Truck Dumping

Starting T.	
Ending T.	

III. Other Information

IV. Observed Data Summary Sheet (Only By Researcher)

	Truck Queuing (Plant)	Truck Loading	Truck Traveling	Truck Queuing (Site)	Truck Dumping	Truck Returning	Truck Washing	**Full Cycle Total T. (min)**	**Traveling Distance (Km)**	**Returning Distance (Km)**

V. Confirmation

A. Collected By

Full Name	Position	Signature	Date

B. Approved By

Full Name	Position	Signature	Date

Post Graduate in Construction Technology and Management

Developing a Model for Minimizing Material Inventory and Dispatching of Ready Mixed Concrete to Sites in Addis Ababa

የተስተዋለው መረጃ ስብስብ ማስገቢያ ቅጽ

የአርማታ ማምረቻ እና የፕሮጀክት መረጃ

	አርማታ ማምረቻ		ፕሮጀክት
ስም		ስም	
ቦታ		ቦታ	
ቀን		የአየር ሁኔታ	

ሀ. አጠቃላይ መረጃ

1. የአርማታዉ መኪና አይነት

ገልባጭ መኪና	

የአርማታዉ መኪና ታርጋ

2. የአርማታዉ አይነት

C-20		C-40	
C-25		C-45	
C-30		C-50	

3. የመጫን አቅም

9 ሜ/ኩ.	
12 ሜ/ኩ.	
ሌላ	

4. መረጃዉ የተሰበሰበበት ሰአት

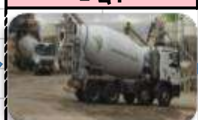
የትራፊክ ጭንቅንቅ ሰዓት	
ከትራፊክ ጭንቅንቅ ነፃ ሰዓት	

5. የኮንክሪት አቀማመጥ ሠራተ

አማካኝ በቁጥር	

ለ. የአርማታ ጭነት መኪና ሙሉ ዑደት መመዝገቢያ ቅጽ

1. አርማታ ለመጫን ወረፋ



የመነሻ ጊዜ	
የማጠናቀቂያ ጊዜ	
የወረፋ ቁጥር	

2. አርማታ መጫን

የመነሻ ጊዜ	
የማጠናቀቂያ ጊዜ	

3. አርማታ ጭኖ መሄድ

የመነሻ ጊዜ	
የማጠናቀቂያ ጊዜ	
መንገድ	

1. አርማታ ለማዉረድ ማመቻቸት

የመነሻ ጊዜ	
የማጠናቀቂያ ጊዜ	

5. አርማታዉን ማራገፍ

የመነሻ ጊዜ	
የማጠናቀቂያ ጊዜ	

6. መኪና ማጠብ

የመነሻ ጊዜ	
የማጠናቀቂያ ጊዜ	

7. አርማታ ለመጫን መመለስ

የመነሻ ጊዜ	
የማጠናቀቂያ ጊዜ	
መንገድ	

8. መኪና ማጠብ

የመነሻ ጊዜ	
የማጠናቀቂያ ጊዜ	

ሐ. ማረጋገጫ

1. የተሰበሰበው በ

ሙሉ ስም	የስራ መደብ	ፊርማ	ቀን

2. ያረጋገጠው ሰው

ሙሉ ስም	የስራ መደብ	ፊርማ	ቀን

Annex-B: - Collected Data Report

A. Overall delivery data for Bole Homes – Gumruk Road Project

Post Graduate in Construction Technology and Management

Thesis on

Concrete to Sites in Addis Ababa

RMC Dispatching Full Cycle Data for Bole Homes - Gumruk Road Project

RMC Dispatching to Site Full Cycle Data for Bole Homes - Gumruk Road Project

Date	Data No	Drivers Name	Truck Code	Truck Capacity (cum)	Delivered Quantity (cum)	Concrete Grade	Loading		Traveling					Traffic Condition		positioning at Site		Dumping		Washing at Site		Returning					Traffic Condition		Washing at Plant		Casting Structure	Event Seen in The Cycle
							Start	Finish	Start	Finish	Odometer Start	Odometer Finish	Route	Jam Hour	Free Hour	Start	Finish	Start	Finish	Start	Finish	Start	Finish	Odometer Start	Odometer Finish	Route	Jam Hour	Free Hour	Start	Finish		Note
9/4/2014	1	ASRES	76107	9.5	9	C30	8:28	8:45	8:45	8:57	87120	87127	C	☐	☑	8:57	9:03	9:03	9:13	9:13	9:30	9:30	9:50	87127	87134.4	C	☐	☑	9:50	10:18	Retaining Wall	
					9																											
9/5/2014	2	ASRES	76107	9.5	3	C25	5:05	5:20	5:20	5:30	87141	87148	C	☐	☑	5:30	5:35	5:35	6:10	6:10	6:30	6:30	6:45	87149	87155.5	C	☐	☑	6:45	7:11	Retaining Wall	
					3																											
9/6/2014	3	ASRES	76107	9.5	9	C30	7:39	7:55	7:55	8:07	87156	87163	C	☐	☑	8:07	8:15	8:15	8:25	8:25	8:40	8:40	8:55	87163	87169.8	C	☐	☑	8:55	9:20	Retaining Wall	
	4	ASRES	76107	9.5	9	C25	9:33	9:50	9:50	10:05	87170	87177	C	☐	☑	10:05	10:10	10:10	10:20	10:20	10:35	10:35	10:55	87177	87184.8	C	☐	☑	10:55	11:26	Retaining Wall	
					18																											
9/8/2014	5	TIBEBU	70945	9.5	5	C25	9:40	9:54	9:54	10:47	59453.4	59469.1	C	☑	☐	10:47	10:59	10:59	11:48	11:48	12:08	12:08	12:55	59469.3	59484.5	C	☑	☐	12:55	1:22	Man Hole	
					5																											
9/9/2014	6	DESALEGN	62223	9.5	8.5	C25	3:21	3:30	3:30	3:45	123703	123710	C	☐	☑	3:45	3:50	3:50	4:50	4:50	5:00	5:00	5:10	123710	123717	C	☐	☑	5:10	5:41	Man Hole	
	7	BIRHANU	62221	9.5	5	C25	6:02	6:15	6:15	7:10	126178.5	126193.3	C	☑	☐	7:10	7:15	7:15	7:35	7:35	7:50	7:50	8:25	126193.4	126207.7	C	☑	☐	8:25	8:56	Retaining Wall	
	8	BIRHANU	62221	9.5	5	C25	8:56	9:10	9:10	10:01	126207.9	126222.6	C	☑	☐	10:01	10:02	10:02	10:26	10:26	10:41	10:41	11:36	126223.4	126237.6	C	☑	☐	11:36	12:06	Retaining Wall	
					18.5																											
9/10/2014	9	BIRHANU	62221	9.5	5	C25	5:57	6:00	6:00	6:55	156246.2	126263.1	C	☑	☐	6:55	6:56	6:56	7:21	7:21	7:31	7:31	8:11	126263.4	126277.7	C	☑	☐	8:11	8:37	Retaining Wall	
	10	TIBEBU	67900	9.5	6	C25	8:00	8:28	8:28	8:46	85146.3	85153.3	C	☐	☑	8:46	8:52	8:52	8:59	8:59	9:10	9:10	9:26	85153.4	85160	C	☐	☑	9:26	9:53	Retaining Wall	
	11	ASRES	76107	9.5	8.5	C25	9:13	9:30	9:30	9:50	87391	87398	C	☐	☑	9:50	10:16	10:16	10:30	10:30	10:50	10:50	11:05	87399	87405.5	C	☐	☑	11:05	11:32	Retaining Wall	
					19.5																											
9/11/2014	12	TIBEBU	67900	9.5	4.5	C25	6:49	7:05	7:05	7:30	85160.2	85169	C	☐	☑	7:30	7:35	7:35	9:46	9:46	10:10	10:10	10:28	85171.4	85177.2	C	☐	☑	10:28	10:53	Curb Stone	
					4.5																											
9/12/2014	13	TIBEBU	67900	9.5	6	C25	2:57	3:14	3:14	3:29	85177.5	85184.2	C	☐	☑	3:29	3:35	3:35	4:46	4:46	5:01	5:01	5:27	85185.1	87192.9	C	☐	☑	5:27	5:53	Curb Stone	
	14	MESAY	62220	9.5	5	C25	3:14	3:25	3:25	4:15	121119	121134	C	☑	☐	4:15	4.35	4.35	5:55	5:55	6:10	6:10	6:45	121134.3	121148.2	C	☑	☐	6:45	7:16	Curb Stone	
	15	BIRHANU	62221	9.5	5	C25	3:52	4:10	4:10	5:05	126309.9	126326.6	C	☑	☐	5:05	6:25	6:25	6:45	6:45	7:00	7:00	7:40	126326.7	126340.8	C	☑	☐	7:40	8:10	Retaining Wall	
	16	MESAY	62220	9.5	5	C25	8:31	8:50	8:50	9:05	121148.5	121165.2	C	☐	☑	9:05	9:15	9:15	10:00	10:00	10:15	10:15	10:55	121165.5	121179.3	C	☑	☐	10:55	11:24	Man Hole	
					21																											
9/13/2014	17	ASRES	76107	9.5	8.5	C25	7:25	7:45	7:45	8:00	87578.1	87585	C	☐	☑	8:00	8:11	8:11	8:46	8:46	9:00	9:00	9:15	87585	87591.8	C	☐	☑	9:15	9:41	Retaining Wall	
	18	TIBEBU	67900	9.5	6	C25	8:00	8:18	8:18	8:34	85249.7	85256.5	C	☐	☑	8:34	8:55	8:55	9:09	9:09	9:24	9:24	9:38	85256.6	85263	C	☐	☑	9:38	10:04	Retaining Wall	
	19	TIBEBU	67900	9.5	6	C25	9:27	10:17	10:17	10:34	85263.1	85269.8	C	☐	☑	10:34	10:43	10:43	10:52	10:52	11:04	11:04	11:18	85270	85276.4	C	☐	☑	11:18	11:45	Retaining	cement ga
	20	GIRMA	75282	9.5	3	C25	9:36	9:55	9:55	10:01	68551.5	68558.5	C	☐	☑	10:01	10:25	10:25	10:45	10:45	10:55	10:55	11:30	68561.5	68568.5	C	☑	☐	11:30	11:58	Retaining Wall	
					23.5																											
9/14/2014	21	BIRHANU	62221	9.5	5	C25	7:22	7:40	7:40	8:35	126385.9	126401.8	C	☑	☐	8:35	8:40	8:40	8:55	8:55	9:10	9:10	9:45	126401.8	126414.7	C	☑	☐	9:45	10:14	Retaining Wall	
	22	BIRHANU	62221	9.5	5	C25	10:21	10:40	10:40	11:05	126415.1	126422	C	☐	☑	11:05	11:06	11:06	11:21	11:21	11:31	11:31	12:01	126422.1	126435.5	C	☑	☐	12:01	12:32	Retaining Wall	
					10																											
9/15/2014	23	BIRHANU	62221	9.5	5	C25	2:25	2:45	2:45	3:35	126428.8	126444	C	☑	☐	3:35	3:40	3:40	3:55	3:55	4:05	4:05	4:55	126444.8	126459.8	C	☑	☐	4:55	5:20	Retaining Wall	
	24	ASRES	76107	9.5	8.5	C25	3:38	3:55	3:55	4:31	87606	87624	C	☑	☐	4:31	4:45	4:45	5:06	5:06	5:20	5:20	5:50	87624	87641.3	C	☑	☐	5:50	6:15	Retaining Wall	
	25	BIRHANU	62221	9.5	5	C25	5:44	6:00	6:00	6:50	126459.9	126475.4	C	☑	☐	6:50	6:55	6:55	7:15	7:15	7:25	7:25	8:10	126475.4	126489.4	C	☑	☐	8:10	8:35	Retaining Wall	
	26	ASRES	76107	9.5	8,5	C25	6:52	7:10	7:10	7:42	87642	87659	C	☑	☐	7:42	7:45	7:45	8:00	8:00	8:15	8:15	8:45	87659	87676.7	C	☑	☐	8:45	9:10	Retaining Wall	
	27	BIRHANU	62221	9.5	5	C25	8:25	8:45	8:45	9:40	126489.6	126503.9	C	☑	☐	9:40	9:45	9:45	10:50	10:50	11:07	11:07	11:40	126503.9	126517.1	C	☑	☐	11:40	12:08	Curb Stone	
	28	ASRES	76107	9.5	8.5	C25	9:28	9:45	9:45	10:30	87677	87697	C	☑	☐	10:30	10:36	10:36	11:30	11:30	11:50	11:50	12:20	87697	87712.7	C	☑	☐	12:20	12:49	Man Hole	
					32																											
9/16/2014	29	BIRHANU	62221	9.5	5	C25	4:07	4:25	4:25	5:15	126546.4	126563	C	☑	☐	5:15	5:16	5;16	5:36	5;36	5:51	5:51	6:41	126563.1	126577	C	☑	☐	6;41	7:11	Retaining Wall	
	30	DESALEGN	62223	9.5	8.5	C25	6:28	6:50	6:50	7:55	124122	124142	C	☑	☐	7:55	8:10	8:10	9:00	9:00	9:10	9:10	10:00	124143	124164	C	☑	☐	10:00	10:30	Man Hole	
	31	BIRHANU	62221	9.5	7	C25	7:57	8:10	8:10	9:35	126577.1	126601.6	C	☑	☐	9:35	9:40	9:40	10:35	10:35	10:50	10:50	11:55	126602.4	126614.9	C	☑	☐	11:55	12:25	Man Hole	
					20.5																											
9/17/2014	32	BIRHANU	62221	9.5	8.5	C25	4:20	4:35	4:35	4:55	126620.9	126627.1	C	☐	☑	4:55	4;56	4;56	5:21	5:21	5;31	5:31	5:51	126627.1	126633.5	C	☐	☑	5:51	6:18	Retaining Wall	
	33	GIRMA	75282	9.5	6	C25	4:29	4:45	4:45	5:00	68691.2	68698	C	☐	☑	5:00	5:10	5:10	5:25	5:25	5:35	5:35	6:00	68698.1	68704.4	C	☐	☑	6:00	6:30	Retaining Wall	
	34	ABEBE	62222	9.5	5	C25	7:20	7:40	7:40	8:20	121083.4	121099.7	C	☑	☐	8:20	8:45	8:45	10:00	10:00	10:15	10:15	11:30	121100	121113.7	C	☑	☐	11:30	12:01	Curb Stone	
	35	BIRHANU	62221	9.5	5	C25	7:25	7:45	7:45	8:35	126633.8	126647.6	C	☑	☐	8:35	9:40	9:40	10:30	10:30	10:45	10:45	11:11	126647.8	126660.9	C	☐	☑	11:11	11:38	Man Hole	
					24.5																											
9/18/2014	36	DESALEGN	62223	9.5	8.5	C30	1:30	1:50	1:50	2:50	124243	124259	C	☑	☐	2:50	3:15	3:15	4:10	4:10	4:20	4:20	4:55	124259	124272	C	☑	☐	4:55	5:23	Man Hole	
	37	ASRES	76107	9.5	9	C30	3:55	4:10	4:10	5:02	87837	87852	C	☑	☐	5:02	5:35	5:35	5:54	5:54	6:15	6:15	6:50	87853	87867.3	C	☑	☐	6:50	7:17	Retaining Wall	
	38	DESALEGN	62223	9.5	9	C30	5:41	6:00	6:00	6:50	124272	124288	C	☑	☐	6:50	7:10	7:10	7:30	7:30	7:45	7:45	8:15	124288	124302	C	☑	☐	8:15	8:43	Retaining Wall	
					26.5																											
9/19/2014	39	BIRHANU	62221	9.5	8	C25	8:30	8:45	8:45	9:10	126701.8	126708	C	☐	☑	9:10	9:11	9:11	9:51	9:51	10:06	10:06	10:31	126708.2	126714.6	C	☐	☑	10:31	10:58	Retaining Wall	
					8																											

9/21/2014	40	DESALEGN	62223	9.5	8.5	C30	2:09	2:30	2:30	2:50	124516	124524	C	☐	☑	2:50	3:40	3:40	4:10	4:10	4:25	4:25	4:40	124524	124532	C	☐	☑	4:40	5:09	Retaining Wall	
	41	BIRHANU	62221	9.5	5	C25	7:08	7:30	7:30	7:45	126824.6	126838.1	C	☐	☑	7:45	7:55	7:55	9:05	9:05	9:20	9:20	9:55	126838.9	126851.4	C	☑	☐	9:55	10:23	Curb Stone	
					13.5																											
9/22/2014	42	ABEBE	62222	9.5	5	C25	3:58	4:15	4:15	4:55	121231.1	121247.2	C	☑	☐	4:55	5:05	5:05	5:20	5:20	5:35	5:35	6:25	121247.5	121261.6	C	☑	☐	6:25	6:50	Retaining Wall	
					5																											
9/23/2014	43	ASRES	76107	9.5	8	C25	7:51	8:10	8:10	8:25	88102	88109	C	☐	☑	8:25	8:30	8:30	8:50	8:50	9:05	9:05	9:30	88109	88115.7	C	☐	☑	9:30	10:01	Retaining Wall	
	44	DESALEGN	62223	9.5	9	C25	8:34	8:50	8:50	9:10	124769	124776	C	☐	☑	9:10	9:11	9:11	9:26	9:26	9:46	9:46	9:56	124776	124788	C	☐	☑	9:56	10:25	Retaining Wall	
					17																											
9/24/2014	45	BIRHANU	62221	9.5	5	C25	4:14	4:30	4:30	5:20	126866.6	126881.9	C	☑	☐	5:20	5:25	5:25	5:45	5:45	6:00	6:00	6:45	126887.1	126894.3	C	☑	☐	6:45	7:16	Retaining Wall	
	46	ASRES	76107	9.5	8.5	C30	7:22	7:35	7:35	8:10	88130	88145	C	☑	☐	8:10	8:25	8:25	9:20	9:20	9:40	9:40	10:05	88145	88159	C	☐	☑	10:05	10:30	Man Hole	
	47	BIRHANU	62221	9.5	5	C25	7:36	7:50	7:50	8:35	126894.8	126909.9	C	☑	☐	8:35	8:40	8:40	9:10	9:10	9:25	9:25	10:10	126910	126922.4	C	☑	☐	10:10	10;36	Retaining Wall	
					18.5																											
9/25/2014	48	BIRHANU	62221	9.5	5	C25	3:11	3:25	3:25	4:15	126956.9	126971.1	C	☑	☐	4:15	4:35	4:35	5:15	5:15	5:30	5:30	6:15	126971.4	126983.8	C	☑	☐	6:15	6:45	Retaining Wall	
					5																											
9/26/2014	49	BIRHANU	62221	9.5	5	C25	2:01	2:15	2:15	3:15	127010.2	127023.5	C	☑	☐	3:15	3:25	3:25	3:50	3:50	4:00	4:00	4:50	127023.7	127035.4	C	☑	☐	4:50	5:20	Retaining Wall	
	50	BIRHANU	62221	9.5	5	C25	5:31	5:45	5:45	6:35	127036.1	127050.9	C	☑	☐	6:35	6:40	6:40	7:20	7:20	7:30	7:30	8:15	127051.2	127063.2	C	☑	☐	8:15	8:42	Retaining Wall	
	51	GIRMA	75282	9.5	3	C25	6:35	6:50	6:50	7:10	68991.2	68998.8	C	☐	☑	7:10	7:11	7:11	8:01	8:01	8:16	8;16	8:36	69002.1	69008.5	C	☐	☑	8;36	9:05	Man Hole	
	52	BIRHANU	62221	9.5	8	C25	8:14	8:30	8:30	9:50	127063.5	127071.8	C	☑	☐	9:50	10:10	10:10	10:35	10:35	10:50	10:50	11:35	127071.9	127079.8	C	☑	☐	11:35	12:06	Retaining Wall	
					21																											
9/27/2014	53	BIRHANU	62221	9.5	5	C25	2:53	3:10	3:10	3:30	127095.5	127103.3	C	☐	☑	3:30	3:31	3:31	4:11	4:11	4:21	4:21	4:51	127103.6	127111.5	C	☑	☐	4:51	5:22	Retaining Wall	
	54	BIRHANU	62221	9.5	5	C25	5:03	5:20	5:20	5:50	127111.5	127119	C	☑	☐	5:50	5:55	5:55	6:20	6:20	6:30	6:30	7:00	127119.3	127126	C	☑	☐	7:00	7:25	Retaining Wall	
	55	TAJU	62224	9.5	5	C25	5:57	6:15	6:15	6:30	124260	124268	C	☐	☑	6:30	7:00	7:00	7:50	7:50	8:00	8:00	8:20	124268	124276	C	☐	☑	8:20	8:46	Man Hole	
	56	BIRHANU	62221	9.5	5	C25	8:15	8:30	8:30	8:53	127126.8	127135.1	C	☐	☑	8:53	9:00	9:00	9:10	9:10	9:20	9:20	9:55	127135.4	127142.8	C	☑	☐	9:55	10:26	Retaining Wall	
	57	TAJU	62224	9.5	5	C25	9:20	9:40	9:40	10:00	124276	124284	C	☐	☑	10:00	10:05	10:05	10:30	10:30	10:45	10:45	11:05	124285	124292	C	☐	☑	11:05	11:34	Retaining Wall	
					25																											
9/28/2014	58	TAJU	62224	9.5	5	C25	3:02	3:45	3:45	3:55	124308	124316	C	☐	☑	3:55	4:05	4:05	4:20	4:20	4:30	4:30	4:45	124816	124324	C	☐	☑	4:45	5:13	Retaining	cement ga
	59	BIRHANU	62221	9.5	5	C25	3:34	3:50	3:50	4:10	127154.4	127167.2	C	☐	☑	4:10	4:15	4:15	4:25	4:25	4:35	4:35	5:10	127167.2	127174.5	C	☑	☐	5:10	5:39	Retaining Wall	
					10																											
9/29/2014	60	TIBEBU	70945	9.5	5	C25	4:13	4:32	4:32	4:48	59878.3	59884.5	C	☐	☑	4:48	5:05	5:05	5:19	5:19	5:31	5:31	5:45	59884.9	59891.6	C	☐	☑	5:45	6:11	Retaining Wall	
	61	MESAY	62220	9.5	5	C25	5:09	5:20	5:20	5:45	122026.7	122033.7	C	☐	☑	5:45	6:00	6:00	6:25	6:25	6:30	6:30	6:45	122033.9	122040.3	C	☐	☑	6:45	7:15	Retaining Wall	
	62	TIBEBU	70945	9.5	5	C25	6:08	6:30	6:30	6:45	59891.8	59898.6	C	☐	☑	6:45	7:09	7:09	7:26	7:26	7:41	7:41	7:55	59899.1	59905.9	C	☐	☑	7:55	8:25	Retaining Wall	
	63	MESAY	62220	9.5	9.5	C25	7:14	7:35	7:35	7:55	122046.7	122047.6	C	☐	☑	7:55	8:40	8:40	9:20	9:20	9:35	9:35	9:50	122048	122054.4	C	☐	☑	9:50	10:21	Retaining Wall	
					24.5																											
9/30/2014	64	DESALEGN	62223	9.5	8.5	C25	7:13	7:30	7:30	7:50	125155	125162	C	☐	☑	7:50	7:51	7:51	9:01	9:01	9:21	9:21	9:36	125165	125173	C	☐	☑	9:36	10:02	Curb Stone	
	65	ASRES	76107	9.5	9	C25	7:41	8:00	8:00	8:10	88390	88400	C	☐	☑	8:10	8:37	8:37	9:10	9:10	9:25	9:25	10:14	88401	88411.7	C	☑	☐	10:14	10:42	Retaining Wall	
	66	TIBEBU	70945	9.5	9	C25	8:08	8:25	8:25	8:46	59935.1	59943.4	C	☐	☑	8:46	9:19	9:19	9:36	9:36	10:47	10:47	11:10	59943.7	59951.7	C	☐	☑	11:10	11:41	Retaining Wall	
					26.5																											
10/1/2014	67	BIRHANU	62221	9.5	5	C25	3:41	4:00	4:00	4:20	127230.9	127237.8	C	☐	☑	4:20	4:25	4:25	4:35	4:35	4:45	4:45	5:10	127237.9	127244.3	C	☐	☑	5:10	5:41	Retaining Wall	
	68	TIBEBU	70945	9.5	5	C25	4:05	4:22	4:22	4:04	59951.9	59959	C	☐	☑	4:04	4:40	4:40	4:50	4:50	4:59	4:59	5:16	59959.1	59965.1	C	☐	☑	5:16	5:46	Retaining Wall	
	69	MESAY	62220	9.5	5	C25	4:16	4:35	4:35	4:55	122100.3	122107.1	C	☐	☑	4:55	5:00	5:00	5:25	5:25	5:30	5:30	6:00	122111.6	122113.6	C	☑	☐	6:00	6:25	Retaining Wall	
	70	ABEBE	62222	9.5	5	C25	4:35	5:30	5:30	5:40	121750.7	121751.6	C	☐	☑	5:40	5:55	5:55	6:10	6:10	6:25	6:25	6:40	121757.9	121764.3	C	☐	☑	6:40	7:07	Retaining	cement ga
	71	ASRES	76107	9.5	8.5	C25	5:34	5:50	5:50	6:08	88500	88508	C	☐	☑	6:08	6:13	6:13	6:45	6:45	7:00	7:00	7:17	88509	88516.7	C	☐	☑	7:17	7:44	Retaining Wall	
	72	BIRHANU	62221	9.5	5	C25	5:36	5:50	5:50	6:10	127244.4	127251.2	C	☐	☑	6:10	6:12	6:12	6:25	6:25	6:35	6:35	7:00	127251.1	127257.7	C	☐	☑	7:00	7:29	Retaining Wall	
	73	ABEBE	62222	9.5	3	C25	7:20	7:35	7:35	7:55	121764.4	121771.4	C	☐	☑	7:55	8:00	8:00	8:20	8:20	8:35	8:35	8:45	121771.9	121778.5	C	☐	☑	8:45	9:11	Retaining Wall	
	74	DESALEGN	62223	9.5	8.5	C30	8:46	9:01	9:01	9:45	125173	125181	C	☑	☐	9:45	9:46	9:46	10:46	10:46	11:01	11:01	11:11	125181	125188	C	☐	☑	11:11	11:36	Man Hole	
	75	BIRHANU	62221	9.5	5	C25	9:22	9:40	9:40	10:00	127258.1	127264.8	C	☐	☑	10:00	10:01	10:01	10:21	10:21	10:31	10:31	10:53	127265.2	127271.2	C	☐	☑	10:53	11:19	Retaining Wall	
	76	TIBEBU	70945	9.5	5	C25	9:40	10:01	10:01	10:17	59970.9	59986.3	C	☐	☑	10:17	10:18	10:18	10:35	10:35	10:47	10:47	11:08	59986.4	59993.3	C	☐	☑	11:08	11:38	Retaining Wall	
					55																											
10/2/2014	77	DESALEGN	62223	9.5	8.5	C25	3:52	4:05	4:05	4:25	125205	125212	C	☐	☑	4:25	4:30	4:30	5:05	5:05	5:20	5:20	5:40	125212	125220	C	☐	☑	5:40	6:08	Retaining Wall	
	78	TAJU	62224	9.5	5	C25	6:29	6:50	6:50	7:05	124440	124448	C	☐	☑	7:05	7:10	7:10	7:45	7:45	8:00	8:00	8:15	124448	124455	C	☐	☑	8:15	8:43	Retaining Wall	
	79	BIRHANU	62221	9.5	5	C25	7:24	7:35	7:35	8:00	127291.9	127299.1	C	☐	☑	8:00	8:01	8:01	8:16	8:16	8:26	8:26	8:51	127299.3	127306.2	C	☐	☑	8:51	9:21	Retaining Wall	
					18.5																											
10/3/2014	80	GIRMA	75282	9.5	4.5	C25	9:48	10:05	10:05	10:30	69140.7	69150.6	C	☐	☑	10:30	10:35	10:35	12:00	12:00	12:15	12:15	12:35	69152.3	69158.5	C	☐	☑	12:35	1:04	Curb Stone	
					4.5																											
10/6/2014	81	BIRHANU	62221	9.5	5	C25	3:45	4:00	4:00	4:20	127439.3	127447	C	☐	☑	4:20	4:21	4:21	4:31	4:31	4:41	4:41	5:11	127447.5	127455.3	C	☑	☐	5:11	5:40	Retaining Wall	
	82	MESAY	62220	9.5	5	C25	5:07	5:25	5:25	5:50	122220.6	122208	C	☐	☑	5:50	5:55	5:55	6:10	6:10	6:25	6:25	6:40	122209	122216.6	C	☐	☑	6:40	7:08	Retaining Wall	
	83	BIRHANU	62221	9.5	5	C25	6:09	6:45	6:45	7:10	127455.7	127463.9	C	☐	☑	7:10	7:40	7:40	8:05	8:05	8:20	8:20	8:50	127464.3	127471.7	C	☑	☐	8:50	9:16	Retaining	cement ga
	84	MESAY	62220	9.5	5	C25	10:09	10:25	10:25	10:45	122216.8	122224.1	C	☐	☑	10:45	10:55	10:55	11:05	11:05	11:20	11:20	11:30	122224.2	122231	C	☐	☑	11:30	11:57	Retaining Wall	
					20																											
10/7/2014	85	ABEBE	62222	9.5	4	C25	1:05	1:20	1:20	1:30	121889.4	121895.3	C	☐	☑	1:30	1:35	1:35	1:45	1:45	2:00	2:00	2:10	121896.2	121902.5	C	☐	☑	2:10	2:36	Retaining Wall	
	86	TAJU	62224	9.5	4	C25	1:09	1:20	1:20	1:35	124578	124584	C	☐	☑	1:35	1:45	1:45	2:30	2:30	2:40	2:40	2:55	124584	124591	C	☐	☑	2:55	3:21	Man Hole	
	87	BIRHANU	62221	9.5	4	C25	1:46	2:00	2:00	2:20	127500.8	127506.7	C	☐	☑	2:20	2:25	2:25	3:30	3:30	3:40	3:40	4:05	127508	127515.8	C	☐	☑	4:05	4:30	Curb Stone	
					12																											
10/14/2014	88	TAJU	62224	9.5	6	C25	9:21	9:35	9:35	9:50	124843	124849	C	☐	☑	9:50	9:55	9:55	11:00	11:00	11:10	11:10	11:25	124849	124855	C	☐	☑	11:25	11:53	Curb Stone	
					6																											
10/17/2014	89	DESALEGN	62223	9.5	8.5	C25	8:20	9:25	9:25	9:45	125942	125950	C	☐	☑	9:45	9:46	9:46	10:46	10:46	11:01	11:01	11:21	125950	125957	C	☐	☑	11:21	11:50	Man Hole	cement ga
					8.5																											
10/18/2014	90	ASRES	76107	9.5	8.5	C25	9:09	9:21	9:21	9:39	89261	89269	C	☐	☑	9:39	10:28	10:28	10:48	10:48	11:05	11:05	11:15	89270	89277	C	☐	☑	11:15	11:46	Retaining Wall	
					8.5																											
10/19/2014	91	MESAY	62220	9.5	9	C25	5:20	5:40	5:40	6:30	122708.6	122724.4	C	☑	☐	6:30	6:35	6:35	7:10	7:10	7:25	7:25	8:30	122724.6	122743.6	C	☑	☐	8:30	8:56	Retaining Wall	
	92	ASRES	76107	9.5	9	C25	7:38	7:55	7:55	8:10	89333.6	89343	C	☐	☑	8:10	8:20	8:20	10:00	10:00	10:15	10:15	10:28	89344	89350	C	☐	☑	10:28	10:58	Curb Stone	
					18																											
10/23/2014	93	MESAY	62220	9.5	7.5	C25	7:06	7:15	7:15	8:05	122776.4	122783.6	C	☑	☐	8:05	8:35	8:35	9:15	9:15	9:30	9:30	9:45	122785.1	122791.1	C	☐	☑	9:45	10:11	Retaining Wall	
					7.5																											
10/24/2014	94	GIRMA	75282	9.5	4	C25	8:28	8:45	8:45	9:05	69775.7	69783.2	C	☐	☑	9:05	9:06	9:06	10:16	10:16	10:31	10:31	10:51	69785.1	69791.5	C	☐	☑	10:51	11:20	Man Hole	
					4																											

10/25/2014	95	TAJU	62224	9.5	8.5	C25	3:25	3:35	3:35	3:50	125399	125406	C	☐	☑	3:50	3:51	3:51	4:11	4:11	4:21	4:21	4:31	125406	125413	C	☐	☑	4:31	4:58	Retaining Wall	
	96	BIRHANU	62221	9.5	8.5	C25	3:40	4:00	4:00	4:20	128256.7	128263.9	C	☐	☑	4:20	4:25	4:25	4:35	4:35	4:50	4:50	5:25	128264.1	128270.6	C	☑	☐	5:25	5:55	Retaining Wall	
	97	MESAY	62220	9.5	8.5	C25	4:00	4:20	4:20	4:45	122792	122799.2	C	☐	☑	4:45	4:50	4:50	5:15	5:15	5:30	5:30	5:45	122799.4	122806	C	☐	☑	5:45	6:14	Retaining Wall	
	98	GIRMA	75282	9.5	4	C25	4:17	4:25	4:25	4:40	69791.6	69798	C	☐	☑	4:40	4:41	4:41	6:56	6:56	7:02	7:02	7:31	69798.9	69805.8	C	☐	☑	7:31	8:00	Curb Stone	
	99	TAJU	62224	9.5	6	C25	5:36	5:45	5:45	6:00	125413	125420	C	☐	☑	6:00	6:05	6:05	6:30	6:30	6:45	6:45	6:55	125421	125427	C	☐	☑	6:55	7:21	Retaining Wall	
					35.5																											
10/30/2014	100	DESALEGN	62223	9.5	8.5	C25	3:51	4:30	4:30	4:45	126487	126493	C	☐	☑	4:45	5:10	5:10	5:30	5:30	5:45	5:45	5:55	126496	126503	C	☐	☑	5:55	6:26	Retaining	cement ga
	101	TAJU	62224	9.5	8.5	C25	4:01	4:20	4:20	4:35	125511	125518	C	☐	☑	4:35	4:50	4:50	5:10	5:10	5:25	5:25	5:40	125518	125525	C	☐	☑	5:40	6:07	Retaining Wall	
	102	ASRES	76107	9.5	9	C25	4:42	4:50	4:50	5:03	89750	89757	C	☐	☑	5:03	5:50	5:50	6:07	6:07	6:10	6:10	6:23	89758	89764.6	C	☐	☑	6:23	6:48	Retaining Wall	
	103	TAJU	62224	9.5	8	C25	6:41	7:00	7:00	7:15	125525	125533	C	☐	☑	7:15	7:20	7:20	8:40	8:40	8:50	8:50	9:05	125535	125542	C	☐	☑	9:05	9:30	Curb Stone	
					34																											
11/8/2014	104	ASRES	76107	9.5	8.5	C25	7:06	7:15	7:15	7:25	89918	89923	C	☐	☑	7:25	7:33	7:33	10:05	10:05	10:20	10:20	10:33	89926	89933.1	C	☐	☑	10:33	11:00	Curb Stone	
					8.5																											
					650																											

B. Overall delivery data for Sansusi – Tatek Kela Road Upgrading Project

Post Graduate in Construction Technology and Management

Thesis on

Developing a Model for Minimizing Material Inventory and Dispatching of Ready Mixed

RMC Dispatching Full Cycle Data for Sansusi - Tatek Kela Road Upgrading Project

RMC Dispatching to Site Full Cycle Data for Sansusi - Tatek Kela Road Upgrading Project

Date	Data No	Drivers Name	Truck Code	Truck Capacity (cum)	Delivered Quantity (cum)	Concrete Grade	Loading Start	Loading Finish	Traveling Start	Traveling Finish	Traveling Odometer Start	Traveling Odometer Finish	Traveling Route	Traveling Traffic Condition Jam Hour	Traveling Traffic Condition Free Hour	Positioning at Site Start	Positioning at Site Finish	Dumping Start	Dumping Finish	Wahing at Site Start	Wahing at Site Finish	Returning Start	Returning Finish	Returning Odometer Start	Returning Odometer Finish	Returning Route	Returning Traffic Condition Jam Hour	Returning Traffic Condition Free Hour	Washing at Plant Start	Washing at Plant Finish	Casting Structure	Event Seen in The Cycle Note
9/4/2014	1	GIRMA	8922	9.5	9	C20	2:24	2:40	2:40	3:50	16582	16608	A	☑	☐	3:50	4:05	4:05	4:50	4:50	5:10	5:10	6:25	16608	16629	A	☑	☐	6:25	6:52	U Ditch	
	2	ASRES	76107	9.5	9	C25	2:42	3:00	3:00	4:15	87072	87094	A	☑	☐	4:15	4:50	4:50	6:20	6:20	6:40	6:40	7:30	87098	87120.7	A	☐	☑	7:30	8:01	Curb Stone	
					18																											
9/5/2014	3	GIRMA	8922	9.5	9	C25	3:21	3:40	3:40	4:45	16658	16687	A	☑	☐	4:45	4:50	4:50	6:50	6:50	7:10	7:10	8:10	16687	16720	B	☐	☑	8:10	8:37	Type B Curb Stone	
	4	ABEBE	62222	9.5	8	C25	4:52	5:10	5:10	6:25	120423.1	120445.5	A	☑	☐	6:25	6:45	6:45	8:00	8:00	8:15	8:15	9:30	120465	120496.4	B	☐	☑	9:30	9:58	Man Hole	
					17																											
9/6/2014	5	ABEBE	62222	9.5	8	C25	7:35	7:50	7:50	9:00	120497.2	120524.8	A	☑	☐	9:00	9:05	9:05	11:00	11:00	11:15	11:15	11:50	120536.1	120557.2	A	☐	☑	11:50	12:15	Type B Curb Stone	
					8																											
9/8/2014	6	ASRES	76107	9.5	9	C25	2:44	3:00	3:00	4:00	87184	87208	A	☐	☑	4:00	4:33	4:33	6:20	6:20	6:40	6:40	7:20	87210	87232.3	A	☐	☑	7:20	7:47	Type B Curb Stone	
	7	GIRMA	8922	9.5	9	C25	3:41	4:00	4:00	5:40	16735	16770	B	☐	☑	5:40	5:50	5:50	7:10	7:10	7:30	7:30	8:45	16771	16806	B	☐	☑	8:45	9:13	Curb Stone	
	8	DESALEGN	62223	9.5	9	C25	4:34	4:50	4:50	6:10	123632	123667	B	☐	☑	6:10	7:00	7:00	8:20	8:20	8:40	8:40	9:45	123668	123702	B	☐	☑	9:45	10:11	Curb Stone	
					27																											
9/9/2014	9	ASRES	76107	9.5	9	C25	2:19	2:35	2:35	3:55	87239	87266	A	☑	☐	3:55	4:23	4:23	6:10	6:10	6:30	6:30	8:15	87277	87310.9	B	☑	☐	8:15	8:45	Type B Curb Stone	
					9																											
9/10/2014	10	ASRES	76107	9.5	8.5	C25	2:41	3:00	3:00	4:15	87318	87354	B	☐	☑	4:15	4:53	4:53	6:45	6:45	7:00	7:00	8:34	87357	87391	B	☐	☑	8:34	9:02	Type B Curb Stone	
	11	DESALEGN	62223	9.5	9	C25	3:03	3:20	3:20	4:40	123731	123764	B	☐	☑	4:40	4:41	4:41	7:01	7:01	7:16	7:16	8:11	123765	123804	B	☐	☑	8:11	8:37	Type B Curb Stone	
					17.5																											
9/11/2014	12	ASRES	76107	9.5	9	C25	2:57	3:12	3:12	4:30	87405	87437	B	☐	☑	4:30	5:10	5:10	6:30	6:30	6:50	6:50	8:30	87439	87467	A	☑	☐	8:30	8:59	Curb Stone	
	13	DESALEGN	62223	9.5	9	C25	4:14	4:30	4:30	6:00	123819	123854	B	☐	☑	6:00	7:00	7:00	8:10	8:10	8:30	8:30	9:45	123855	123892	B	☐	☑	9:45	10:13	Man Hole	
					18																											
9/13/2014	14	ASRES	76107	9.5	8	C25	2:13	2:30	2:30	3:20	87522	87545	A	☐	☑	3:20	3:40	3:40	5:20	5:20	5:35	5:35	6:28	87551	87578.1	A	☐	☑	6:28	6:55	Type B Curb Stone	
	15	DESALEGN	62223	9.5	8	C25	6:14	6:30	6:30	8:15	123953	123987	B	☐	☑	8:15	8:16	8:16	10:11	10:11	10:26	10:26	11:41	123989	124024	B	☐	☑	11:41	12:07	Type B Curb Stone	
					16																											
9/15/2014	16	DESALEGN	62223	9.5	8	C25	4:40	5:00	5:00	6:00	124024	124047	A	☐	☑	6:00	6:10	6:10	6:55	6:55	7:20	7:20	8:00	124047	124070	A	☐	☑	8:00	8:25	U Ditch	
					8																											
9/17/2014	17	DESALEGN	62223	9.5	9	C25	2:52	3:10	3:10	4:05	124165	124204	B	☐	☑	4:05	4:06	4:06	7:11	7:11	7:31	7:31	8:46	124204	124242	B	☐	☑	8:46	9:11	Type B Curb Stone	
	18	ASRES	76107	9.5	9	C25	3:50	4:05	4:05	5:28	87765	87796	B	☐	☑	5:28	6:00	6:00	9:00	9:00	9:20	9:20	10:30	87809	87837.5	A	☑	☐	10:30	10:55	Type B Curb Stone	
					18																											
9/19/2014	19	DESALEGN	62223	9.5	9	C25	6:44	7:00	7:00	8:00	124309	124332	A	☐	☑	8:00	8:05	8:05	8:50	8:50	9:10	9:10	10:25	124232.4	124256	A	☑	☐	10:25	10:51	U Ditch	
					9																											
9/20/2014	20	TAJU	62221	9.5	8	C25	2:27	2:45	2:45	4:10	123846	123882	B	☐	☑	4:10	4:11	4:11	5:41	5:41	5:56	5:56	7:21	123882	123918	B	☐	☑	7:21	7:52	Curb Stone	
	21	DESALEGN	62223	9.5	8	C25	3:51	4:10	4:10	5:20	124445	124480	B	☐	☑	5:20	5:21	5:21	6:41	6:41	6:56	6:56	8:01	124480	124516	B	☐	☑	8:01	8:31	Curb Stone	
					16																											
9/21/2014	22	DESALEGN	62223	9.5	9	C25	5:12	5:30	5:30	6:50	124532	124567	B	☐	☑	6:50	6:51	6:51	8:11	8:11	8:26	8:26	10:01	124568	124602	B	☐	☑	10:01	10:32	Curb Stone	
	23	ASRES	76107	9.5	9	C25	6:05	6:20	6:20	8:00	87984	88019	B	☐	☑	8:00	8:05	8:05	9:55	9:55	10:15	10:15	11:42	88019	88056.1	B	☐	☑	11:42	12:09	Type B Curb Stone	
					18																											
9/23/2014	24	DESALEGN	62223	9.5	8	C25	1:04	1:20	1:20	2:20	124691	124715	A	☐	☑	2:20	2:55	2:55	5:20	5:20	5:35	5:35	6:25	124731	124769	B	☐	☑	6:25	6:51	Type B Curb Stone	
	25	ASRES	76107	9.5	8	C25	6:45	7:00	7:00	7:50	88056	88079	A	☐	☑	7:50	7:55	7:55	8:50	8:50	9:05	9:05	9:50	88080	88102.4	A	☐	☑	9:50	10:21	Man Hole	
					16																											
9/25/2014	26	ASRES	76107	9.5	9	C25	6:17	6:30	6:30	7:30	88189.4	88217.3	A	☐	☑	7:30	8:25	8:25	9:30	9:30	9:45	9:45	10:45	88217.4	88248.1	B	☐	☑	10:45	11:11	Man Hole	
					9																											
9/26/2014	27	DESALEGN	62223	9.5	9	C25	1:12	1:30	1:30	3:00	124992	125026	B	☐	☑	3:00	3:10	3:10	6:45	6:45	7:10	7:10	7:50	125028	125058	B	☐	☑	7:50	8:18	Type B Curb Stone	
	28	ASRES	76107	9.5	9	C25	6:44	7:00	7:00	7:45	88248.1	88274	A	☐	☑	7:45	7:55	7:55	8:55	8:55	9:10	9:10	10:00	88274.4	88310	B	☐	☑	10:00	10:26	Man Hole	
					18																											
9/29/2014	29	ASRES	76107	9.5	8	C25	7:20	7:35	7:35	8:40	88326	88348	A	☑	☐	8:40	9:00	9:00	9:45	9:45	10:00	10:00	11:05	88350	88378.9	A	☑	☐	11:05	11:32	U Ditch	
	30	DESALEGN	62223	9.5	8	C25	8:06	8:20	8:20	9:15	125105	125127	A	☐	☑	9:15	9:50	9:50	10:30	10:30	10:41	10:41	12:10	125128	125155	A	☑	☐	12:10	12:39	U Ditch	
					16																											
10/1/2014	31	ASRES	76107	9.5	9	C25	3:14	3:35	3:35	4:55	88411	88446	B	☐	☑	4:55	5:10	5:10	7:40	7:40	8:00	8:00	9:28	88453	88483.6	B	☐	☑	9:28	9:53	Type B Curb Stone	
					9																											
10/2/2014	32	DESALEGN	62223	9.5	9	C25	7:03	7:20	7:20	8:45	125220	125256	B	☐	☑	8:45	9:40	9:40	11:10	11:10	11:30	11:30	12:45	125257	125294	B	☐	☑	12:45	1:13	Curb Stone	
					9																											
10/3/2014	33	ASRES	76107	9.5	8	C25	2:45	3:00	3:00	4:00	88516	88539	A	☐	☑	4:00	4:03	4:03	5:00	5:00	5:10	5:10	6:00	88539	88561.8	A	☐	☑	6:00	6:31	Man Hole	
	34	DESALEGN	62223	9.5	8	C25	3:02	3:20	3:20	4:25	125294	125317	A	☑	☐	4:25	4:55	4:55	5:20	5:20	5:35	5:35	6:20	125317	125339	A	☐	☑	6:20	6:46	U Ditch	
					16																											
10/4/2014	35	DESALEGN	62223	9.5	9	C25	4:24	4:40	4:40	6:00	125339	125374	B	☐	☑	6:00	6:01	6:01	7:16	7:16	7:26	7:26	8:46	125374	125409	B	☐	☑	8:46	9:14	Man Hole	
	36	BIRHANU	62221	9.5	9	C25	4:29	4:50	4:50	6:30	127360	127398.7	B	☐	☑	6:30	6:35	6:35	8:10	8:10	8:25	8:25	9:55	127412.8	127438	A	☑	☐	9:55	10:26	Curb Stone	
					18																											
10/7/2014	37	DESALEGN	62223	9.5	9	C25	4:24	4:40	4:40	6:15	125496	125531	B	☐	☑	6:15	7:20	7:20	9:55	9:55	10:10	10:10	12:00	125540	125576	B	☑	☐	12:00	12:26	Type B Curb Stone	
					9																											

10/9/2014	38	ASRES	76107	9.5	9	C25	3:11	3:25	3:25	4:50	88785	88824	B	☐	☑	4:50	5:08	5:08	6:12	6:12	6:30	6:30	7:57	88824	88858.5	B	☐	☑	7:57	8:23	Man Hole	
					9																											
10/12/2014	39	DESALEGN	62223	9.5	9	C25	2:10	2:30	2:30	3:50	125739	125777	B	☐	☑	3:50	4:00	4:00	5:30	5:30	5:50	5:50	6:50	125778	125812	B	☐	☑	6:50	7:19	Curb Stone	
	40	ASRES	76107	9.5	9	C25	2:27	2:45	2:45	3:44	89005	89032	A	☑	☐	3:44	3:45	3:45	4:31	4:31	4:51	4:51	5:31	89036	89058.1	A	☐	☑	5:31	5:56	U Ditch	
					18																											
10/13/2014	41	DESALEGN	62223	9.5	8	C25	5:03	5:20	5:20	6:35	128813	128843	B	☐	☑	6:35	6:36	6:36	7:41	7:41	7:51	7:51	8:31	125844	125869	A	☐	☑	8:31	9:02	Man Hole	
	42	ASRES	76107	9.5	8	C25	5:20	5:35	5:35	7:00	89114	89152	B	☐	☑	7:00	7:20	7:20	9:00	9:00	9:20	9:20	10:25	89154	89188.4	B	☐	☑	10:25	10:55	Type B Curb Stone	
					16																											
10/14/2014	43	DESALEGN	62223	9.5	8	C25	2:52	3:10	3:10	4:30	125869	125905	B	☐	☑	4:30	4:31	4:31	6:31	6:31	6:46	6:46	7:46	125906	125941	B	☐	☑	7:46	8:11	Type B Curb Stone	
					8																											
10/18/2014	44	ASRES	76107	9.5	9	C25	2:13	2:30	2:30	3:24	89277	89302	A	☐	☑	3:24	3:45	3:45	5:12	5:12	5:35	5:35	6:45	89307	89333.3	A	☑	☐	6:45	7:16	Curb Stone	
	45	NIGUSE	62223	9.5	9	C25	2:58	3:45	3:45	4:45	125958.1	125986	A	☐	☑	4:45	5:00	5:00	6:45	6:45	7:00	7:00	8:00	125990.1	126017.9	A	☑	☐	8:00	8:29	Type B Curb	cement ga
					18																											
10/19/2014	46	ABEBE	62222	9.5	8	C25	1:49	2:05	2:05	3:10	122328.2	122358.2	B	☐	☑	3:10	3:35	3:35	4:15	4:15	4:30	4:30	5:30	122359.3	122385.9	A	☑	☐	5:30	5:56	U Ditch	
	47	ASRES	76107	9.5	9	C25	2:34	2:50	2:50	3:50	89350	89384	B	☐	☑	3:50	4:05	4:05	5:40	5:40	6:00	6:00	6:50	89386	89411.4	A	☐	☑	6:50	7:18	Curb Stone	
	48	BIRHANU	62221	9.5	8	C25	3:39	4:00	4:00	5:20	128055.6	128094.4	B	☐	☑	5:20	5:21	5:21	6:36	6:36	6:51	6:51	8:31	128096.4	128131.1	B	☑	☐	8:31	9:01	Man Hole	
	49	TAJU	62224	9.5	9	C25	4:00	5:05	5:05	6:15	125124	125156	B	☐	☑	6:15	6:30	6:30	8:40	8:40	8:55	8:55	10:00	125166	125203	B	☐	☑	10:00	10:27	Type B Curb	cement ga
	50	ABEBE	62222	9.5	9	C25	7:04	7:20	7:20	8:35	122386.1	122419.3	B	☐	☑	8:35	8:40	8:40	9:45	9:45	10:00	10:00	11:00	122420.1	122448.7	A	☑	☐	11:00	11:28	Man Hole	
					43																											
10/20/2014	51	ASRES	76107	9.5	8	C25	2:36	2:55	2:55	4:00	89411	89438	A	☑	☐	4:00	4:10	4:10	5:00	5:00	5:20	5:20	6:39	89440	89468.1	A	☑	☐	6:39	7:05	U Ditch	
					8																											
10/22/2014	52	DESALEGN	62223	9.5	8	C25	2:46	3:00	3:00	4:30	126227	126263	B	☐	☑	4:30	4:31	4:31	6:31	6:31	6:51	6:51	7:51	126270	126294	A	☑	☐	7:51	8:22	Type B Curb Stone	
	53	ABEBE	62222	9.5	8	C25	3:50	4:05	4:05	5:35	122495	122525.9	B	☐	☑	5:35	5:45	5:45	8:15	8:15	8:30	8:30	9:30	122530	122554	A	☑	☐	9:30	10:00	Type B Curb Stone	
					16																											
10/24/2014	54	ASRES	76107	9.5	9	C25	6:33	6:50	6:50	8:00	89525	89551	A	☑	☐	8:00	8:15	8:15	10:20	10:20	10:40	10:40	12:06	89564	89594	B	☐	☑	12:06	12:37	Type B Curb Stone	
					9																											
10/25/2014	55	ASRES	76107	9.5	8	C25	3:21	3:40	3:40	4:43	89600	89621	A	☐	☑	4:43	4:54	4:54	5:53	5:53	6:15	6:15	7:05	89622	89643.7	A	☐	☑	7:05	7:36	Man Hole	
	56	DESALEGN	62223	9.5	9	C25	4:00	4:20	4:20	5:03	126336	126362	A	☐	☑	5:03	5:30	5:30	7:15	7:15	7:30	7:30	8:33	126371	126404	B	☐	☑	8:33	9:04	Type B Curb Stone	
	57	ASRES	76107	9.5	9	C25	8:45	9:05	9:05	9:58	89644	89668	A	☐	☑	9:58	10:05	10:05	11:20	11:20	11:40	11:40	12:30	89668	89692.8	A	☐	☑	12:30	12:59	Man Hole	
					26																											
10/28/2014	58	TAJU	62224	9.5	8	C25	2:38	2:55	2:55	4:20	125428	125467	B	☐	☑	4:20	4:35	4:35	6:45	6:45	7:05	7:05	8:30	125478	125510	B	☐	☑	8:30	9:00	Type B Curb Stone	
	59	ASRES	76107	9.5	8	C25	3:07	3:25	3:25	4:44	89693	89715	A	☑	☐	4:44	4:50	4:50	6:40	6:40	7:00	7:00	8:00	89722	89750.2	A	☑	☐	8:00	8:28	Type B Curb Stone	
					16																											
10/29/2014	60	ABEBE	62222	9.5	8	C25	3:20	3:40	3:40	4:40	122650.5	122672.9	A	☐	☑	4:40	4:50	4:50	6:35	6:35	6:50	6:50	8:00	122673.6	122696.2	A	☑	☐	8:00	8:29	Type B Curb Stone	
	61	DESALEGN	62223	9.5	8	C25	3:47	4:00	4:00	5:40	126404	126441	B	☐	☑	5:40	5:45	5:45	8:25	8:25	8:40	8:40	9:40	126458	126489	B	☐	☑	9:40	10:08	Type B Curb Stone	
					16																											
10/30/2014	62	GIRMA	8922	9.5	8.5	C25	5:01	5:20	5:20	6:35	20555	20584	A	☑	☐	6:35	7:50	7:50	9:50	9:50	10:00	10:00	11:00	20594	20626	B	☐	☑	11:00	11:28	Type B Curb Stone	
					8.5																											
11/7/2014	63	GIRMA	8922	9.5	8.5	C25	3:53	4:10	4:10	5:20	20801	20823	A	☑	☐	5:20	6:30	6:30	8:20	8:20	8:35	8:35	9:30	20832	20865	B	☐	☑	9:30	9:59	Type B Curb Stone	
					8.5																											
11/8/2014	64	GIRMA	8922	9.5	8.5	C25	4:32	4:50	4:50	6:00	20866	20888	A	☑	☐	6:00	6:25	6:25	9:00	9:00	9:20	9:20	10:20	20895	20922	A	☑	☐	10:20	10:49	Type B Curb Stone	
					8.5																											
11/12/2014	65	ASRES	76107	9.5	8	C25	5:27	5:45	5:45	6:55	90013	90043	B	☐	☑	6:55	7:37	7:37	9:35	9:35	9:55	9:55	11:55	90050	90083.4	B	☑	☐	11:55	12:21	Type B Curb Stone	
					8																											
11/14/2014	66	TAJU	62224	9.5	7	C25	6:23	6:40	6:40	7:55	125955	126002	B	☐	☑	7:55	8:00	8:00	10:50	10:50	11:05	11:05	12:20	126005	126036	B	☐	☑	12:20	12:49	Type B Curb Stone	
					7																											
11/16/2014	67	GIRMA	8922	9.5	7	C25	5:28	5:50	5:50	7:30	21270	21293	A	☑	☐	7:30	7:35	7:35	9:30	9:30	9:45	9:45	10:45	21300	21330	B	☐	☑	10:45	11:11	Type B Curb Stone	
					7																											
11/19/2014	68	GIRMA	8922	9.5	7	C25	3:13	3:30	3:30	5:20	21330	21365	B	☑	☐	5:20	5:21	5:21	7:31	7:31	7:46	7:46	9:11	21367	21398	B	☐	☑	9:11	9:40	Type B Curb Stone	
	69	ABEBE	62222	9.5	8	C25	7:37	7:55	7:55	9:10	123224.7	123254.7	B	☐	☑	9:10	9:20	9:20	9:55	9:55	10:10	10:10	11:50	123256.6	123284.4	A	☑	☐	11:50	12:18	U Ditch	
					15																											
11/21/2014	70	GIRMA	8922	9.5	7	C25	3:04	3:25	3:25	5:30	21399	21435	B	☑	☐	5:30	5:35	5:35	7:30	7:30	7:45	7:45	9:00	21448	21478	B	☐	☑	9:00	9:28	Type B Curb Stone	
					7																											
11/22/2014	71	GIRMA	8922	9.5	7	C25	3:32	3:50	3:50	5:30	21478	21513	B	☐	☑	5:30	5:40	5:40	8:20	8:20	8:35	8:35	9:45	21520	21546	A	☑	☐	9:45	10:13	Type B Curb Stone	
					7																											
11/23/2014	72	GIRMA	8922	9.5	6	C25	3:08	3:25	3:25	4:50	21550	21586	B	☐	☑	4:50	5:10	5:10	5:40	5:40	6:00	6:00	7:40	21588	21624	B	☑	☐	7:40	8:05	U Ditch	
					6																											
11/25/2014	73	GIRMA	8922	9.5	6	C25	5:25	5:40	5:40	7:00	21624	21656	B	☐	☑	7:00	7:20	7:20	9:50	9:50	10:15	10:15	11:10	21644	21693	B	☐	☑	11:10	11:36	Type B Curb Stone	
					6																											
11/27/2014	74	GIRMA	8922	9.5	6	C25	3:11	3:25	3:25	5:00	21694	21729	B	☐	☑	5:00	5:15	5:15	7:55	7:55	8:10	8:10	9:10	21737	21764	A	☑	☐	9:10	9:41	Type B Curb Stone	
					6																											
11/28/2014	75	GIRMA	8922	9.5	7	C25	4:39	5:00	5:00	6:20	21764	21790	A	☑	☐	6:20	6:30	6:30	8:40	8:40	9:00	9:00	9:50	21799	21827	A	☐	☑	9:50	10:15	Type B Curb Stone	
					7																											
11/29/2014	76	ABEBE	62222	9.5	7	C25	3:19	3:35	3:35	4:35	123314.1	123342.2	A	☐	☑	4:35	4:50	4:50	7:25	7:25	7:40	7:40	9:15	123345	123377.5	B	☐	☑	9:15	9:42	Type B Curb Stone	
					7																											
11/30/2014	77	GIRMA	8922	9.5	7	C25	2:49	3:05	3:05	4:10	21828	21855	A	☑	☐	4:10	5:00	5:00	7:15	7:15	7:35	7:35	9:00	21867	21902	B	☐	☑	9:00	9:28	Type B Curb Stone	
					7																											
12/3/2014	78	GIRMA	8922	9.5	6	C25	6:47	7:05	7:05	8:00	21905	21932	A	☐	☑	8:00	8:05	8:05	9:10	9:10	9:25	9:25	10:20	21935	21967	B	☐	☑	10:20	10:48	Man Hole	
					6																											
					644																											

Annex-C: - Cost Breakdown for the Raw Materials (2014 E.C.)

NO	Type of Materials	Unit	2014 2nd quarter (Selling Price)
1	Sand (hauling distance more than 5 km in Addis Ababa)	m3	906.25
2	Gravel 02	m3	875.00
3	Red Ash	m3	450.00
4	Stone	m3	777.78
5	Red Brick	pcs	10.06
1	Cement (PPC)	Qt	497.50
2	Cement (OPC)	Qt	560.00

NO	Type of Materials	Unit	2014 3rd quarter (Selling Price)
	CEMENT		
1	Sand (hauling distance more than 5 km in Addis Ababa)	m3	1031.25
2	Gravel 02	m3	1031.25
3	Red Ash	m3	468.75
4	Stone	m3	777.78
5	Red Brick	pcs	15.00
6	Cement (PPC)	Qt	880.00
7	Cement (OPC)	Qt	942.50
8	Selected Material	m3	312.50

NO	Type of Materials	Unit	2014 4th Q. (birr)
1	Cement (PPC)	Qt	515.66
2	Cement (OPC)	Qt	655.78
3	Sand	m^3	1050.00
4	Gravel 02	m^3	1043.48
5	Red Ash	m^3	430.00
6	Stone	m^3	750.00

Annex-D: - Summary of Annual Concrete Delivery to Sites (2014 E.C.)

Supplied to Site Name	Concrete Grade in m^3							Total (m^3)
	C-15	**C-20**	**C-25**	**C-30**	**C-35**	**C-40**	**C-50**	
A.A River Crossing	-	-	6	-	-	-	-	6
Legedadi Water Project	35	150.5	1450	31.5	-	-	-	1667
Bole Michael Road Project	250.5	9.5	244.5	4961.5	-	62	-	5528
Gummruk Bole Homes	209.5	-	6549	735	-	-	-	7493.5
Tatek Sansusi	14	-	5289	203	-	-	-	5506
Tuludimtu Kality	-	-	300.5	75	-	-	-	375.5
Asphalt Plant	-	-	14	-	-	-	-	14
Inrich Agro Industry	-	-	-	35	-	-	-	35
Samcon Engineering	-	-	641	-	182.5	-	-	823.5
Concrete Batching Plant	9.5	-	25.5	-	-	-	-	35
T.N.T Construction	-	-	-	373.5	-	-	-	373.5
Santa Maria	-	-	180	651.5	-	-	115	946.5
G.B.H AACRA Chaka Park	-	-	711	44	-	-	-	755
G.B.H AACRA Kotebe	-	-	175.5	347	-	-	-	522.5
G.B.H AACRA Jemo	-	-	182.5	-	-	-	-	182.5
G.B.H AACRA Kechene	-	-	24.5	-	-	-	-	24.5
Central Garaj	-	-	6.5	-	-	-	-	6.5
G.B.H AACRA Hamza Bridge	-	-	-	167	-	-	-	167
G.B.H AACRA Gofa-Kera	-	-	45	-	-	-	-	45
Markan Construction	-	-	-	176	-	-	-	176
G.B.H AACRA Ferencay	-	-	35	400	-	-	-	435
G.B.H AACRA Noel Slab Culvert	-	-	12	-	-	-	-	12
G.B.H AACRA Nasew Real State	-	-	78.5	-	-	-	-	78.5
G.B.H AACRA Entoto	-	-	68	60	-	-	-	128
Tamrin Trading	-	-	68	-	-	-	-	68
Head Office	-	-	7	-	-	-	-	7
C.B.P Construction	-	-	126	-	-	-	-	126
Bole Apartment	-	-	4.5	-	-	-	-	4.5
Total								**25541.5**