DISSERTATION

RAW MATERIAL OPTIMIZATION AND CO_2 SENSITIVITY-PREDICTIVE ANALYTICS IN CEMENT MANUFACTURING: A CASE STUDY AT UNION BRIDGE PLANT, HEIDELBERG MATERIALS, MARYLAND

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ABSTRACT

RAW MATERIAL OPTIMIZATION AND CO_2 SENSITIVITY-PREDICTIVE ANALYTICS IN CEMENT MANUFACTURING: A CASE STUDY AT UNION BRIDGE PLANT, HEIDELBERG MATERIALS, MARYLAND

Cement has been in use by humans throughout history, and its manufacturing process has undergone many changes. The high increase in economic growth around the world and the demand for rapid infrastructure development due to population growth are the underlying reasons for the globally high cement demand. Cement is produced by grinding clinker together with a mixture of ground gypsum. The clinker is produced using a rotary kiln which burns a mixture of limestone, clay, magnesium, silica, and iron with desired atomic percentages through the calcination process. The quarry serves as the main source of raw material for the rotary kiln in cement production. Over the years cement manufacturing has hurt environmental, social, and political aspects of society. This negative impact includes the overuse of raw material which is obtained by mining resulting in disturbed landmass, overproduction of rock waste material, and the emission of CO_2 resulting from the calcination of limestone in the pyro process. The study looks at three cement manufacturing systems and uses different methodologies to achieve results that can be implemented in the cement industry. These three systems were (1) the quarry (2) the preheat tower and (3) the kiln.

Ensuring the consistency of material feed chemistry, with the quarry playing a pivotal role, is essential for optimizing the performance of a rotary kiln. The optimization of the raw material also allows limited use of raw materials for cement manufacturing, cutting down waste. The study employed a six-step methodology, incorporating a modified 3D mining software modeling tool, a database computer loop prediction tool, and other resources to enhance mining sequencing, optimize raw material utilization, and ensure a consistent chemistry mix for the kiln. By using overburden as a raw material in the mix, the quarry nearly universally reduced the environmental impact of squandering unwanted material in the quarry. This has a significant environmental impact since it requires less space to manage the overburdened waste generated during mining. In addition, raw material usage was optimized for clinker production, causing a reduction of 4% in sand usage as raw material, a reduction in raw material purchase cost, a reduction of the variability of kiln feed chemistry, and the production of high-quality clinker. The standard deviation

of kiln feed LSF experienced a 45 percent improvement, leading to a 65 percent reduction in the variability of kiln feed.

The study also uses machine learning methods to model different stages of the calcination process in cement and to improve knowledge of the generation of CO_2 during cement manufacturing. Calcination plays a crucial role in assessing clinker quality, energy requirements, and CO_2 emissions within a cement-producing facility. However, due to the complexity of the calcination process, accurately predicting CO_2 emissions has historically been challenging. The objective of this study is to establish a direct relationship between CO_2 generation during the raw material manufacturing process and various process factors. In this paper, six machine-learning techniques are explored to analyze two output variables: (1) the apparent degree of oxidation, and (2) the apparent degree of calcination. Sensitivity analysis of CO_2 molecular composition (on a dry basis) utilizes over 6000 historical manufacturing health data points as input variables, and the findings are utilized to train the algorithms. The Root Mean Squared Error (RMSE) of various regression models was examined, and the models were then run to ascertain which independent variables in cement manufacturing had the largest impact on the dependent variables. To establish which independent variable had the biggest impact on CO_2 emissions, the significance of the other factors was also assessed.

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DEDICATION

To

Gladys Tandoh Boakye, Nanadwoa Sarpomaah Boakye, Kwabena Asamoah Boakye and Kwaku Abakah Boakye Jr.

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Chapter 1 – Introduction

After water, cement is the material that is used the most on Earth. Concrete is made from it, and it is essential to many facets of society, such as buildings, roads, bridges, dams, and sidewalks. Modern infrastructure is built on the backs of the cement and concrete industries. Therefore, it is a major area of focus for industrial decarbonization initiatives and has a significant worldwide impact on both energy demand and carbon emissions. The high level of foreign trade in these goods highlights the connection between cement and concrete production and societal progress. Therefore, it is anticipated that future market demand will show opposing tendencies in industrialized and emerging nations. Demand in emerging and developing nations will continue to climb to suit the requirements of growing, increasingly urban populations, while demand in Europe, for example, is predicted to decline after being stable for many years, as noted by Uratani and Griffiths [1]. This chapter of research work examines the background of cement manufacturing throughout history, the definition of the challenges, the need for a solution, and the objectives of the research project.

1.1 Background

Hydraulic cements are widely used and essential building materials since they are the binding agent in most mortars and concretes. Hydraulic cement is defined as cement that has the capacity to consolidate and harden either below or in the presence of additional water. This is because of the minerals or chemical components that comprise cement hydrating. Even though it's been a long tradition, it's still unknown who invented or employed which variety of cement in the first place. Still, a general timeline of developments might be drawn; much of the following synopsis comes from [2-6].

1.1.1 Brief history of hydraulic cement

Mud binders, either with or without straw, were the first binder used in masonry construction and are still in use today in many regions of the world, mostly for adobe construction. A natural asphalt known as bitumen was utilized as a binder in some regions of ancient Mesopotamia. True mortars were used for a long time in ancient Egypt, Greece, and Crete. Lime mortars were created in Greece and Crete, much like they are today, by burning limestone. The Egyptians, on the other hand, made some lime mortars and mostly used rudimentary gypsum (plaster) mortars since they had easy access to limestone. Since gypsum is far scarcer than limestone and takes much higher temperatures to convert to plaster, the Egyptians appear to have used gypsum instead of limestone mostly due to a lack of fuel. Some ancient Egyptian building foundations were also constructed with gypsum concrete [7], in which the coarse aggregates were produced from construction detritus or limestone from quarries. Hydraulic lime from impure limestones was used in some Greek mortars; in other cases, lime was combined with specific volcanic ash, mainly from the island of Thíra (or Thera; today known as Santorin or Santorini) and also Atlantis.

Thíra has been linked to the myth of Atlantis in certain historical discussions. However, it is important to acknowledge that this speculation remains a subject of ongoing debate and lacks confirmation.

Although the Greeks taught the ancient Romans about a variety of mortar types, the Romans are generally credited with developing hydraulic cement because they enhanced the quality and application techniques of hydraulic mortars and used them far more extensively. The most important was the Roman usage of cements containing volcanic ash and pozzolan-lime. Large amounts of volcanic ash, specifically preferred by the Romans for this use, were extracted from the distant slopes of Mount Vesuvius in the vicinity of Pozzuoli village. Based on the name of this village, this substance became known as pozzolana (also spelled puzzolana, pouzzolana, or pozzuolana); similarly, the more general terms pozzolan and pozzolanic were used. All volcanic ashes with pozzolanic characteristics, including Santorin earth and trass, are now referred to as pozzollana. The Romans used broken tiles or potshards as a fake pozzolan in places where pozzolana was not accessible; the Greeks may have similarly used crushed ceramics earlier.

The strength of the Roman pozzolan-lime cements allowed for a large increase in the proportion of aggregates in the mortars compared to unmodified lime mortars. One might even combine coarse aggregates, which are typically leftover from demolition projects, to create concrete, a mass building ingredient. Throughout the Roman Empire, pozzolan-lime mortars and concrete were employed by Roman engineers for a variety of purposes. These included the construction of sea walls for artificial harbors and the waterproof lining of aqueducts, among other structures, with the most well-known surviving example of which is probably the Pantheon in Rome.The Pantheon is an iconic example of Roman concrete construction, a renowned temple, rather than an aqueduct. During the first few centuries after the fall of the Roman Empire, the quality of hydraulic mortars and concretes was worse due to either a lack of pozzolans in some areas or a lack of understanding of the processes involved in making cement and lime. But the regular lime mortars seem to have survived better. There was still a sporadic interest in duplicating the ancient Roman cement's quality, and in Western Europe during the 18th century, active research was being conducted to raise the cement's grade.

John Smeaton's research when he was given the contract in 1756 to construct a replacement lighthouse on the Eddystone Rocks, offshore from Plymouth, England, led to a significant advancement in the knowledge of hydraulic cement. Smeaton experimented to create a mortar for this project that could survive particularly harsh maritime conditions. Smeaton found that limestones containing significant levels of clay may be calcined to produce strong 3 hydraulic lime mortar. His main discovery was the connection between the clay component and the development of hydraulic character. It was a hydraulic lime-pozzolan mortar (that is, hydraulic lime made from Aberthaw, Wales limestone and Italian pozzolana) that he used to build the new Eddystone lighthouse, which stood for 126 years before needing to be replaced. He discovered that an even better mortar could be made by combining this hydraulic lime with pozzolans. In 1791, Smeaton reported the findings of his study on hydraulic lime.

In 1796, a patent was granted to James Parker (Joseph Parker in some writeups) in England for hydraulic cement made from argillaceous limestone nodules (septaria). In just a few years, the deceptive but enduring name "Roman cement" began to be used to describe cement made from a range of argillaceous limestones. The new material had no pozzolana and was compositionally very different from its namesake, but the name was predicated on the assertion that it was as good as and had a comparable reddish color to, the ancient Roman product. The new cement, better known as *natural cement*, gained popularity quickly due to its superior strength, hydraulic qualities, and quick set and hardening. Up until the middle of the 19th century, natural cement was the most common type of cement made in England and most of Europe. The necessity for waterproof mortars for the lining and lockworks of the Erie Canal in New York provided the first impetus for the subsequent development of cement production in the United States compared to Europe. The canal's construction got underway in 1817, and the following year, argillaceous limestone deposits along the canal were found to be excellent for making natural cement. Not long after, natural cement started to be manufactured. Locals referred to the argillaceous limestone as cement rock. When cement rock resources were later found in eastern Pennsylvania and other locations, the natural cement business in the United States flourished rapidly. The only cement produced in the US up until the early 1870s were slag-lime and natural cement, which were mostly created from slag from quenched iron furnaces.

Due to variances in raw material composition and processing techniques, natural cement in the United States and Europe showed notable regional variations in quality. Research into methods to enhance the quality and/or lessen the variability of natural cements was sparked by Smeaton's discovery of the significance of clay to the formation of hydraulic character in lime mortars. An eventually more significant line of inquiry was the production of "artificial cement." Louis J. Vicat, a French engineer, was arguably the most important researcher in this field. His work was initially published in 1818 and demonstrated how high-quality hydraulic limes could be created from regular limestone if certain amounts of shale or clay were added, even in the absence of argillaceous limestones or cement rock. 1828 saw the publication of a more thorough analysis, which was translated into English in 1837 [8].

Smeaton, Vicat, and other researchers' results seem to have been pretty widely shared, and several patents for different kinds of hydraulic lime and cement were granted in England and France. Edgar Dobbs was granted a patent in England in 1810 for a cement that contained lime, road dust made of limestone, and clay. The Dobbs patent expired in 1824, and it's possible that this served as motivation for Leeds, England-based bricklayer, and inventor Joseph Aspdin to submit a patent application for a product that looked similar at first glance later that year. Aspdin patented Portland Cement, a product he named, on December 15, 1824, under the title "An improvement in the modes of producing an artificial stone" (British patent 5022). This moniker referred to Portland stone, a highly valued, extremely durable dimension stone that is quarried on the Portland Island in South Dorset. By today's standards, Aspdin's patent is intriguing because it provides surprisingly little precise information on the product or how it was made; in fact, it appears to be a very shaky starting point for a potentially significant industry! Soon after getting his patent, Aspdin opened the first portland cement (the word is no longer capitalized) plant in Wakefield, England. Afterwards, William Aspdin, his son, planted plants in Gateshead-on-Tyne and along the Thames. The pricey new cement struggled to overtake the highly valued natural cements in the early years of the British portland cement business. The selection of portland cement for the prominent Thames River tunnel construction project in 1838 gave the material's marketing a significant boost.

Early attempts by others to match the quality of Aspdin's portland cement were mainly futile and gave rise to rumors that crucial information about the cement's production was missing from Aspdin's patent, maybe on purpose. However, by the middle of the 1840s, the duplicating efforts had produced crucial insights into what those missing features were. Chief among them was the realization that the raw materials in the kiln needed to be heated to temperatures far higher than those required to calcine the limestone. The finding that over-burned, partially vitrified material (previously rejected) from the kilns produced better-quality cement served as empirical evidence for this; competitor cement manufacturer Isaac C. Johnson is mostly credited with bringing attention to the necessity of high temperature burning. Eventually, it was discovered that the presence of hydraulic dicalcium silicate and, more crucially, tricalcium silicate (explained in more detail later) in the vitrified material (clinker) was the source of the improvement in cement quality. Whether the original Aspdin portland cement was a well-made hydraulic lime based on heat-activated clay pozzolans or if it included any of these minerals is still up for contention. It is now shown that Joseph Aspdin's later portland cements included both dicalcium silicate and (minor) tricalcium silicate [9,10], and that his son's cements also contained these silicates. Over the ensuing decades, several advancements were achieved in England and abroad to the mineralogic composition and production process of portland cement through trial and error. Modern portland cements are very different from those made in the middle to late 19th century, and improvements are continuously being made. The industry has continued to use the name "Portland Cement" mostly because it still refers to an artificial cement composed of raw materials such as limestone and argillaceous elements and because the name has an unparalleled cachet.

About 1855, the first portland cement factories outside of England were built in Belgium and Germany. Imports of Portland cement into the United States started in the late 1860s and peaked in 1895 at over 0.5 million metric tons (Mt), after which they started to decline as a result of rising domestic output. David Saylor founded the nation's first portland cement mill in Coplay, Pennsylvania, in 1871. Natural cement had been produced there since 1850. The first portland cement produced at Coplay was of low quality. Nonetheless, Saylor was producing high-quality goods by 1875 after mostly resolving issues with low kilning temperatures and insufficient raw material mixing. Because portland cement was so good, more and more Portland cement factories were built around the country. Lesley [5] gives a thorough account of the history of the country's early portland cement industry, which lasted until roughly 1920. In the United States, portland cement production increased significantly starting around 1890. The United States' production of natural and slag-lime cements reached a combined total of 1.46 million tons by 1900, surpassing 1.22 million tons for the first time. A current overview picture of a typical cement factory is shown in Figure 1.

Figure 1 Overview of Heidelberg Materials Cement Plant Union Bridge [11]

1.1.2 Growth of the market for Portland cement

The development of reinforced concrete in the late 1860s greatly increased demand for concrete overall. Because concrete is relatively weak in tension but robust in compression, the invention of adding reinforcing steel bar to increase tensile strength allowed for the construction of high-rise buildings and suspended slab structures (like bridge decks). All the early chimney-style or vertical shaft kilns produced portland and natural cements in batches. The rotary kiln, which was invented in 1873, represented a significant advancement in raw material heating and mixing efficiency as well as output capacity. An enhanced rotating kiln design, developed in 1885 by English engineer F. Ransome, permitted continuous material processing. The first high-capacity rotary kilns were created by Thomas Edison in 1902; his kilns measured roughly 46 meters (m) in length, compared to the previous rotary kilns' 18 to 24 meters. The use of concrete and cement manufacturing increased sporadically around the world throughout the first half of the 20th century, with significant dips during the two World Wars and the Great Depression. Nonetheless, cement production has grown steadily and strongly since World War II, reaching roughly 2 Gt of output in 2004 as previously mentioned. Very few nations in the world nowadays do not have at least one cement plant. Figure 1 illustrates how, since 1990, cement output has grown at the fastest rate in Asia, where it today makes up over half of global production. China has been largely responsible for Asia's overall growth and currently, India is also driving the expanded growth. Portland cement or closely comparable cement using Portland cement as a basis makes up most of the cement manufactured worldwide today.

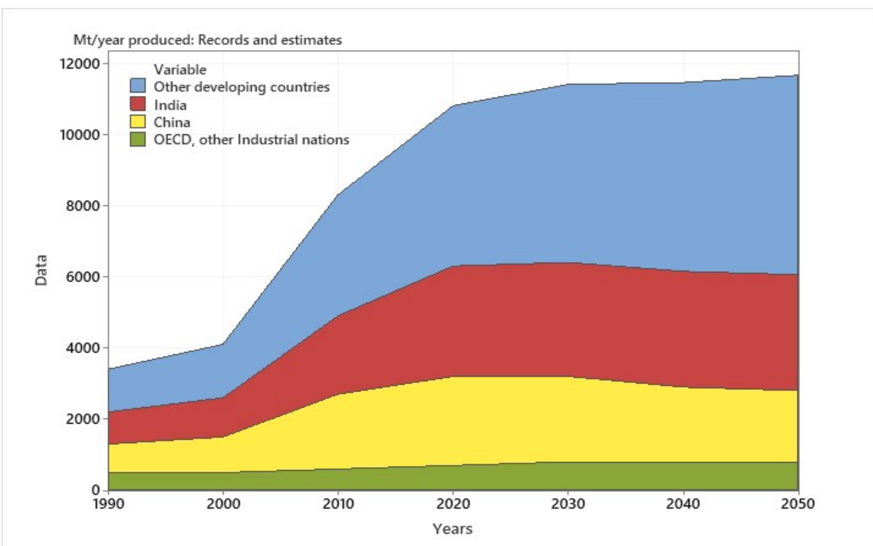


Figure 2 Projection of Cement Usage Until 2050 [12]

The combination of the fast-increasing population and a shift in construction preferences toward concrete is mostly responsible for the overall growth. Other underlying causes of the rising cement demand internationally include the strong increase in economic growth globally and the need for quick infrastructure development because of population growth [13]. As a result, the production of cement is growing rapidly [14]. Global living standards are significantly raised by the industry, which also benefits affiliated industries by creating direct jobs and other benefits. Even though there are a lot of significant positive impacts of cement over generations, the production of cement has also harmed society, politics, and the environment over time. These issues are satisfactorily covered in the ensuing sections of this Chapter. This research intends to address some of these negative impacts and novel ways to address them.

1.2 Problem Description

As mentioned in this chapter, cement is the most used material next to water. Over a generation, civilizations have depended on cement for industrialization and modernization. As mentioned in this chapter, even though cement plays a key role in civilization, the manufacturing of cement has had a negative impact. Some of these negative impacts are:

1. Cement manufacturing is linked to significant raw material extraction. Excessive extraction of raw material from the ground is used in cement manufacturing. Limestone which forms the main constituent for cement manufacturing is obtained by mining. The public has been concerned about the environmental effects of mineral extraction. There is currently a lot of interest around the world in mining and its sustainability, with a focus on the need to move the mining industry to a more sustainable framework. The world of manufacturing depends on the raw materials that are extracted through mining operations. When making cement, the external raw material—silica, for instance—is added to the mixture as a chemistry correction factor. These illustrate the importance of mining to the cement sector. Unfortunately, loss of natural resources and destruction of ecosystems are among the social and environmental issues brought on by mining. The fact that most developing nations use illicit methods to carry out these mining operations is another growing issue regarding the effects on the environment. For instance, the phrase "sand mafia" has been used to describe the well-documented, terrible socioeconomic impact of sand mining on the environment in most third-world nations, such as India [15]. Some of the effects of illicit sand mining on Indian rivers and beaches were also

mentioned in the article [15]. These included: (1) biodiversity losses; (2) land declines; (3) a reduction in the ability to withstand extreme events such as river floods, coastal storms, and marine currents; (4) changes in the availability of water due to pollution and a lowering of the water table; (5) damaged infrastructure, such as embankments; and (6) changes in landforms and landscapes. An additional concern is the destabilization of the local cement industry and the unethical practices adopted by procurement personnel to competitively price source their cement. Most poor nations still engage in this illicit sand mining today. Furthermore, a comparable finding on the societal effects of sand mining was noted [16].

2. Generation of waste dumps as a by-product of the extraction of raw material. This waste which is normally overburden material that cannot be used for cement manufacturing is dumped as stockpiles. Waste management is a global environmental challenge. The largest global waste producer is the mineral industry [16]. An estimated 50 times more material volume is generated as mining waste, which entails significant environmental risks and liabilities. When overburden is removed to reveal minerals or ore—limestone in the case of cement manufacturing—mining operations typically produce large volumes of solid waste. Waste dumps or minefields are used to store the overburden. The surface water quality is eroded and occasionally impacted by these trash dumps. The loss and deterioration of natural areas are other detrimental effect of mining waste on the ecosystem. These landfills also encompass large regions that might be put to better use. The secret is to employ cutting-edge planning tools to reduce the overburden volumetric removal and to use the material as an in-situ raw material alternative for other raw materials used in the cement manufacturing process.
3. Emission of CO_2 during the manufacturing process has been one of the greatest environmental concerns for cement manufacturing. The production of cement is associated with significant emissions of harmful air pollutants, which are known to cause various health hazards. The cement industry ranks as the third largest contributor to industrial air pollution, including substances like sulfur dioxide, nitrogen oxides (NOx), and carbon monoxide." [17]. In the evaluation of these problems associated with cement manufacturing, the most apparent one that has the greatest effect on society is the emission of CO_2 which is part of the greenhouse emission. According to research conducted by Mahlia [18] and Zhang et al. [19], they assert that human activities, particularly the emissions of greenhouse gases (GHGs), are the primary cause of global warming, leading to potentially catastrophic consequences if not effectively controlled and mitigated. Global warming

is widely recognized as one of the most significant environmental and economic threats of our era. Despite its widespread acceptance and success, the cement industry must confront the challenges related to GHG emissions and prioritize long-term sustainability, as highlighted by Mishra and Siddique [14]. Unfortunately, technological advances have made it possible to make greater volumes of cement than in the past. which is attributed to higher production levels as the root cause [20]. Figure 3 shows that the cement industry contributes about 7-8% of the world's CO_2 emission.

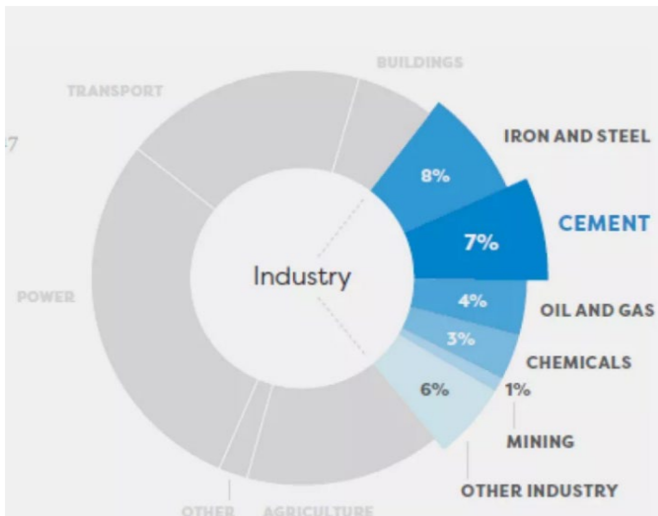


Figure 3 Share of global CO_2 emissions that come from cement production (2017 data) [17]

As mentioned herein, there are problems associated with cement manufacturing. These problems have impact on the environment and need to be addressed. For years the cement industrial has done it best to be environmentally friendly and has operated to meet governmental regulations as prevised. In recent years, the industry has been under a lot of scrutiny on whether more can be done. Finding solutions to the current trend of digitization and a data-driven world is becoming increasingly important. The question is what some of the solutions are that can be employed. This study looks at ways in which problems mentioned herein can be addressed with novel solutions.

1.3 Need for Solution

Most of the cement manufacturing companies face a global business environment that is becoming increasingly competitive. As a result, they look for ways to cut production costs without sacrificing product quality. Some of these opportunities, however, include reducing the outsourcing of raw materials without reducing the quality of the material. Outsourcing has some social and political impacts around the world because of the illegal ways mining these materials is performed, and because of how it impacts society. Therefore, they are always looking at how to reduce raw material waste associated with the mining of limestone from quarries and reducing the outsourcing of material. In cement manufacturing, the quarry is the main source of raw material fed to the rotary kiln. The raw material feed is first ground at the microscale in the raw mill and calcined before feeding to the rotary kiln. Approximately 70% to 85% of the raw materials necessary for the kiln's operation are provided by the quarry. The remaining 20% to 30% consists of raw materials like clay, silica, and iron, which are typically sourced externally and come at a higher cost. In mining, the limestone's large natural lands are disturbed, and waste is generated from overburden that cannot be used. This affects the ecosystem. It is therefore advantageous to use more local materials, such as material sources from the quarry which is normally wasted. There will be less need for raw materials like sand and fewer big areas created for overburden garbage dumps the more natural quarry in-situ material that can be used in the raw material mix for cement. The waste dumps generated from mining can sometimes expose sulfur-bearing overburden and can be active sources of acid generation with the potential to severely contaminate soils, surface, and groundwater, and endanger both local and downstream ecosystems. Finding a solution to reduce the volumetric need for sand as raw material for cement manufacturing will have an impact on illegal activities in developing countries. The lower the demand for sand as raw material for cement manufacturing due to the use of other substitute materials, the less the need for sand as raw material. The key is to reduce the disturbed mining areas, reduce the amount of wasting dumps, and reduce outsourcing of raw materials.

Global warming is widely recognized as one of the gravest environmental and economic threats facing our present-day world. The cement industry must deal with the impact on GHS and long-term sustainability notwithstanding its acceptance and success [14]. Since 1880, the mean global temperatures have increased by about 1 degree Celsius (1.7° degrees Fahrenheit). The global temperature is expected to increase by approximately 1.5 degrees Celsius (equivalent to 2.7 degrees Fahrenheit) by the year 2050, with projections indicating a further rise of 2 to 4 degrees Celsius (equivalent to 3.6 to 7.2 degrees Fahrenheit) by the end of the century. Air temperatures on Earth have been rising since the Industrial Revolution began in earnest circa 1800. While natural fluctuations contribute to some extent, the majority of evidence suggests that human activities, notably the release of greenhouse gases that trap heat, are predominantly responsible for the warming of our planet. Climate-related consequences are already negatively affecting public health, manifesting in air pollution, disease outbreaks, extreme weather occurrences, displacement of communities, psychological stress, and heightened food insecurity in regions unable to produce or access an adequate food supply. Cement production is associated with substantial extraction of raw materials, resulting in environmental impacts, extensive use of fossil fuels, and significant CO_2 emissions. The calcination process received increasing attention from both the government and the public in recent years since this is the primary source of CO_2 in the cement industry [21]. Calcination is a complex industrial process inherent to cement manufacturing, characterized by the interplay of mass transfer, heat transfer, and chemical and physical transformations.

The chemical and physical characteristics of materials can be changed by heating them to high temperatures. The calcination of limestone produces 60% of the CO_2 emissions, with 0.5 tons of CO_2 emitted per ton of clinker produced [22]. Significant amounts of CO_2 are created by the cement industry (about 0.59 tCO_2 per ton of cement produced in 2020) [23] and it is one of the industries that, in the context of current climate policy, presents the greatest challenges for quantifying CO_2 emissions and eventual decarbonization [24]. As mentioned by Czigler et al. [17], the cement industry alone produces the most CO_2 emissions per dollar of revenue and is responsible for nearly a quarter of all industry CO_2 emissions. Around 7-8% of the CO_2 emissions in the world come from cement factories, and each ton of cement produced results in the release of 900 kg of CO_2 into the environment. In their study, they examined worldwide efforts and potential solutions aimed at reducing CO_2 emissions from cement production. Concurrently, various parties have explored novel approaches to decrease the carbon footprint within the cement industry's manufacturing processes. To better manage CO_2, the cement manufacturing industry must better understand the source of the CO_2 in the manufacturing process and how to quantify it.

1.4 Goals, Research Questions, and Contributions

The main objective of this research is to determine whether systems engineers can use operational data from fielded cement manufacturing systems as feedback loop data to inform the iterative life cycle management process in the operational and sustainment phase of the cement manufacturing process. This goal encompasses a wide range of research areas, so the scope of the study has been further expanded to include elements about quarry operation, raw material, preheat tower, and kiln systems. Additionally, given the existing policy and guidelines, the research will be scoped to discover feasible techniques that working-level cement manufacturing plants can each individually adopt.

1.4.1 Statement of Research Questions

To accomplish the goals outlined in the previous section, research questions were identified. The specific research questions for this report are as follows:

- Can improving "kiln feed chemistry by consistent quarry material mix" help with the negative environmental impact of raw material demand and reduce waste dump stockpile size?
- Can a machine learning algorithm be used to predict CO_2 using a cement manufacturing historic production variables dataset?

It is hypothesized that a link exists between cement performance data; and that proper analysis and review of this data can be leveraged to positively influence system performance. The expectation is that this research will contribute a set of specific recommendations or methods that the working-level cement industry can use to improve manufacturing system performance. The research will determine what factors, if any, have an impact on quarry raw material usage, the reduction of outsourcing raw materials, the reduction of overburden waste generated during quarry mining, and individual input variables that affect CO_2 emission during the calcination of limestone in cement manufacturing. Cement manufacturing can adopt findings from this research work to positively influence enterprise system performance.

1.4.2 Contributors

This research will add to the corpus of knowledge in systems engineering in multiple ways, enhancing current procedures for complicated cement manufacturing system life cycle management. A helpful model for systems engineering procedures in cement manufacture that are suited to the operations and sustainability phase of life cycle management is offered by this research. To demonstrate the importance of feedback loops among stakeholders, the model links a continuous improvement loop with the conventional systems engineering Vee model. Additionally, the study offers a fresh connection between operational data and data on cement production and operational performance metrics. Systems engineers can operate within the current limitations of labor, time, and other resources thanks to the research study. Lastly, this study shows a novel way to estimate CO_2 using manufacturing historical data and optimize quarry raw material utilizing current methods.

1.4.3 Assumptions/Limitations

This research will be accomplished utilizing the existing historical manufacturing data that is collected, stored, and used. The goal of this research is not to establish or refute the validity of the metrics that have been gathered and examined by regulatory requirements. It should be mentioned that this study was conducted on a single cement plant, to expand its findings to include additional cement plants in the future. Heidelberg Material US, Union Bridge facility is the cement facility under consideration. The data used for this research work was approved by Heidelberg Materials US, Union Bridge plant. This research aims to produce actionable recommendations for feedback data to positively influence overall enterprise system performance by resolving specific parts issues at the lowest working level while utilizing the current data collection systems, manpower, and other resources.

Chapter 2 – Literature Review and Existing Method

An analysis of pertinent cement manufacturing processes as well as independent research on the performance of the cement manufacturing system were carried out to determine a methodical approach to the resolution of the problems mentioned in Chapter 1.

2.1 Cement Manufacturing

The intricate process of making cement starts with the mining and subsequent grinding of raw materials, such as clay and limestone, into a fine powder known as raw meal. This meal is then fired in a cement kiln to a sintering temperature of up to 1450 °C. The raw materials' chemical bonds are broken during this process, and the constituent parts are subsequently reassembled to form new compounds. Clinker, which are rounded nodules ranging in size from 1 to 25 millimeters, is the product. To make cement, the clinker is ground into a fine powder in a cement mill and combined with gypsum. After that, water and aggregates are combined with powdered cement to create concrete that is used in buildings. The mix of the raw materials determines the clinker quality, which needs to be regularly checked to guarantee cement quality. For example, excess-free lime causes unfavorable outcomes such as volume expansion, longer setting times, or decreased strength. To guarantee process control at every stage of the cement manufacturing process, including clinker generation, several online and laboratory technologies can be used. The process of making cement is intricate and needs several systems and subsystems. Significant raw material extraction is required to produce cement, which hurts the environment and requires a lot of fossil fuel energy and CO_2 emissions. Raw elements including limestone, chalk, shale, clay, iron, and sand are used to make cement. The main sources of these resources are quarried, crushed, finely powdered, and blended to the exact chemical makeup which is normally called the meal. The meal is supplemented with largely external raw components [25]. Following the mining, grinding, and homogenization of the raw materials, calcination involves burning the resulting calcium oxide at high temperatures along with silica, alumina, and ferrous oxide to form clinker. The clinker is then ground or milled in conjunction with additional ingredients (such as slag, gypsum, etc.) to create cement [26]. It has long been known that one of the primary industrial processes contributing to rising carbon emissions is the manufacturing of cement. The first chemical reaction of $CaCO_3$ breakdown to CaO and CO_2 and the large-scale combustion of mostly fossil fuels are the two main sources of carbon dioxide production during this process [21]. Of key import are the causes of CO_2 emissions in cement plants. The three production steps that go into creating cement are raw material preparation, clinker production (pyro-processing), and clinker grinding and mixing. Cement production is a labor-intensive and difficult process. From the source of raw materials to the finished product, cement, Figure 4 depicts the schematic structure of a cement factory [27]. An in-depth discussion of the steps of the process manufacturing of cement is presented herein.

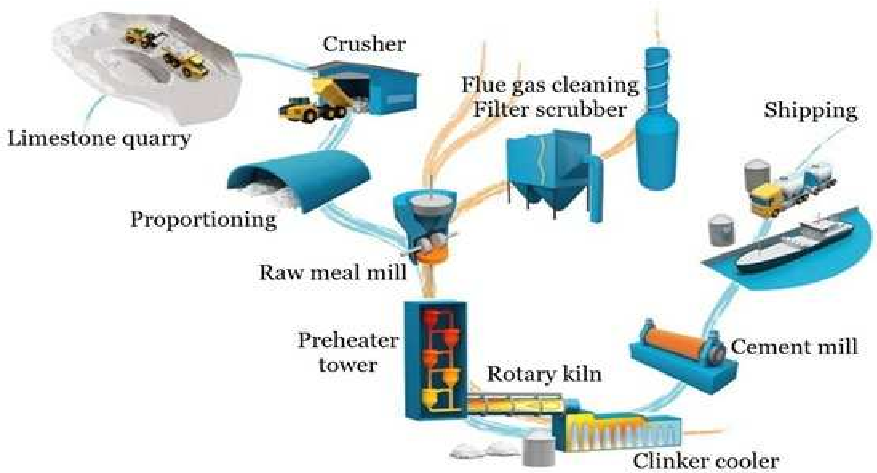


Figure 4 Diagram of the general procedure at the cement plant. Adapted from [27].

2.1.1 Limestone Quarrying

An open pit mine where dimension stone, rock, riprap, sand, gravel, or slate are extracted from the earth is called a quarry. In many jurisdictions, regulations are in place to control the hazards to public safety and minimize the environmental effects of quarries [28]. The first step in the manufacturing of cement is quarrying. Most of the raw materials used to make cement are made of limestone. Although underground mining is an option, open-face quarries are the most popular way to extract limestone [29]. Most cement factories are located close to quarries to save the expense of transporting raw materials. Drilling is used in exploration to gain subterranean access to the raw material. Geological models are developed using computer models to assess the limestone concentration based on the exploration data. Along with the extraction of limestone, overburden a useless material that needs to be removed and discarded is also evaluated with the aid of the model. The unusable overburden waste needs to be kept in a sizable surface area, maybe in large amounts. Due to their unstable state, these quarry waste dumps hurt the environment, pose a risk of pollution, and typically detract from the aesthetics of surrounding areas. Economic mine plans are created by computer software modeling simulations to maximize the quarrying process. Measurements of chemistry quality control, geotechnical stability requirements, and economic factors are important input elements for the models.

The material is transported to a storage dome after being drilled, shot, loaded, carried, and crushed. The mining planning phases' flowchart, which uses mining economic models to accomplish the most efficient quarry development before production, is shown in Figure 5 This enables a detailed study to verify the feasibility of the quarry project.

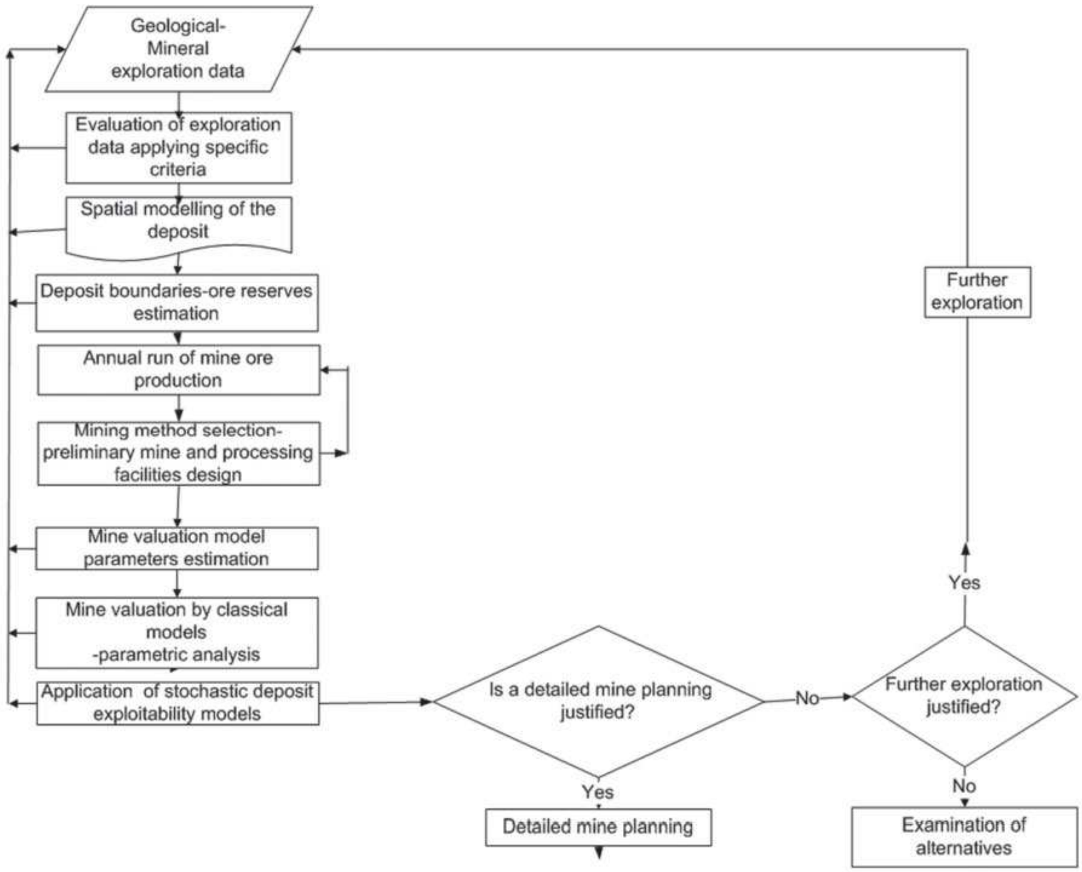


Figure 5Flowchart of mine planning stages about mining economic models [30]

Typically, 80–95% of the raw materials used to make cement are limestone [29]. Drilling is a technique used in subsurface exploration to obtain raw materials. Geological models are created using software to ascertain the concentration of limestone in each location. The model is also used to assess the overburden, or waste material, that must be removed and discarded with the limestone. Huge mechanical devices like loaders and haul trucks are used to finish the limestone mining process. Sourcing of most of the extra raw materials required is contracted out. Magnesium carbonate, silica, alumina, iron oxide, and limestone make up most of the basic materials used to make cement. As blended raw meal feed, the combined material is first ground and crushed. According to Mujumdar et al. [31] the powdered feed normally has a grain size of 50 mm and the appropriate composition. The combined raw material is fed into the kiln for pyroprocessing after passing through the preheat tower. Table 1 displays the feed's usual composition.

Table 1 Typical composition of cement raw material

Ref.	Composition (% wt)										
	CaO	SiO_2	Al_2O_3	Fe_2O_3	MgO	K_2O	SO_3	Na_2O	H_2O	Organics	Loss Ignition
Kakali et al. [32]	43.11	13.76	3.23	2.45	0.55	0.28	0.00	0.00	0.00	0.00	35.42
Engin and Ari [33]	40.74	13.55	4.10	2.60	2.07	0.30	0.56	0.08	0.50	0.90	34.60
Galbenis and Tsimas [34]	41.95	13.55	3.31	2.55	1.98	0.41	0.00	0.00	0.00	0.00	35.12
Kabir et al. [35]	43.61	13.29	3.83	1.95	0.50	0.79	0.23	0.06	0.20	0.00	35.45
Benhelal et al. [21]	41.51	14.03	3.39	2.54	2.59	0.57	0.30	0.24	0.00	0.00	34.83

The raw meal recipe is computed using the basic cement industry modules, silica modulus (SM), alumina modulus (AM), and lime saturation factor (LSF). LSF is the ratio of limestone to other ingredients in a recipe; it is generally given as a weight percentage.

$$LSF = 100 \cdot CaO/(2.8 \cdot SiO_2 + 1.18 \cdot Al_2O_3 + 0.65 \cdot Fe_2O_3)$$

When the cement clinker has an LSF value of 100, the percentage of the primary strength-giving calcium silicate alite reaches its maximum. LSF values for industrial clinker usually range from 94 to 98 weight percent. SM and AM influence the kiln's energy requirements and the quality of the cement clinker [27].

$$SM = SiO_2/(Al_2O_3 + Fe_2O_3)$$

$$AM = Al_2O_3/Fe_2O_3$$

Figure 6 shows the general layout of an existing limestone quarry at New Windsor owned by Heidelberg Material, United States. The layout includes crushers, conveyors chutes, and screens to help reduce the size of blasted material from boulders into smaller sizes of about minus 5 inches. The layout also shows the waste dump which was created because of the overburden removed during the mining process. The material is loaded using a loader, excavator, and shovel. The material is loaded into trucks and hauled into a crusher hopper.

Figure 6 shows a typical layout of a limestone quarry at New Windsor Maryland belonging to Heidelberg Materials

2.1.2 Raw Meal and Blending Silo

The quality of the limestone that is mined determines how much raw meal is fed into the raw milling machine. Maintaining the threshold limit of undesired oxides while maintaining continuous quality parameters of suitable oxides for cement manufacturing is the aim of cement plant operation [36]. The quality of the quarry is determined by the material's geological chemical makeup. The deposit may contain other minerals that are unsuitable for use in the manufacture of cement. High magnesium concentrations in the limestone make it unsuitable for use in the production of cement. In other situations, the deposit might be combined with very alkaline deposits that are unsuitable to produce cement. Additionally, a significant amount of topsoil and improper soil must be removed to expose limestone with the right chemistry for use in the production of cement. This limestone is then held in stockpiles, which hurts the environment, as previously mentioned. Most of the time, it is preferable to handle the inappropriate material by gradually combining it with limestone as a raw material, which will displace part of the necessary outsourcing material. As previously indicated, the extra outsourcing material is made up of iron (Fe_2O_3) from slag if it cannot be obtained from the quarry, alumina (Al_2O_3) from clays, and silica (SiO_2) from sand mining. Raw meal is a mixture of limestone, iron (Fe_2O_3) from slag, alumina (Al_2O_3) from clays, and silica (SiO_2) from sand mining. Since the quality of the limestone supplied by the quarry cannot be guaranteed, if the limestone is directly extracted from a portion of the quarry, thorough quality control (QC) measures must be taken [37]. It is necessary to mix (or blend) the limestone in the quarry to obtain uniform quality [38, 39]. The presence of some undesirable components in raw meal mix might lower the efficiency of the cement plant if th eir concentration is beyond certain threshold limits. The most significant ingredient is magnesium oxide (MgO), which, at low concentrations, acts as a fluxing agent. At concentrations higher than 3.5 percent, though, it enters the cement as an impurity. Alkalinity, which is determined by [Na]eq, is an additional undesired component. Table 2 shows the percentage of raw meals used as feed for the raw mill in the mixture. The raw meal material mix percentage for the Union Bridge Cement Plant is displayed in this table. The quarries and quality department are responsible for ensuring that the standard deviation is kept under control and that these goals are met.

Table 2 Raw meal material mix percentages

Raw Meal Material Mix	Percentage of Mix
Total Limestone (T)	82.8%
Total Iron (T)	0.5%
Total Sand (T)	6.8%
Total Fly Ash (T)	0.0%
Total Ponded Ash (T)	9.9%

To ensure that the volume and chemistry are regulated for the kiln exactly and consistently, the material mix is managed using feeders and a Gammetrix analyzer. Table 3 lists the chemistry goals for the raw meal and quarry. To contribute to the production of high-quality clinker and cement, certain goals must be reached. A typical target needed for the Union Bridge Cement Plant of Heidelberg Materials USA is displayed in Table 3.

Table 3 Dependent chemistry quality measurable variables with expected controlled limits and standard deviations

Dependent Chemistry Variables	Quarry (%)			Raw Mill (%)		
	LL	MID	UL	LL	MID	UL
LSF	400	650	900	99	102	105
AR				1.35	1.4	1.45
SR				2.55	2.65	2.75
Na[eq]	0.25	0.35	0.45	0.30	0.35	0.40
Mag	2.0	3.0	4.0	1.95	2.1	2.25
K2O	0.31	0.38	0.45	0.40	0.45	0.50
Al2O3				2.8	2.9	3.0
Standard Deviation	250			3		

The second stage of the cement-making process is raw milling. In a raw mill, raw materials are ground into "raw meal" to create cement. After being fed into a cement kiln, raw meal is turned into clinker, which is subsequently processed in a cement mill to create cement. To increase dryness, the raw material can be ground in ball mills or vertical mills using hot gas. The limestone from the quarry is combined with sand, clay, and iron to create the proper chemical composition needed at the raw mill to make cement. The mixture is fed into a blending silo, which continuously combines the ingredients to increase the homogeneity of the raw meal material. This enhances the material's chemistry mix's uniformity. An end discharge ball mill that is typically used as the raw mill to grind raw meal is depicted in Figure 7.

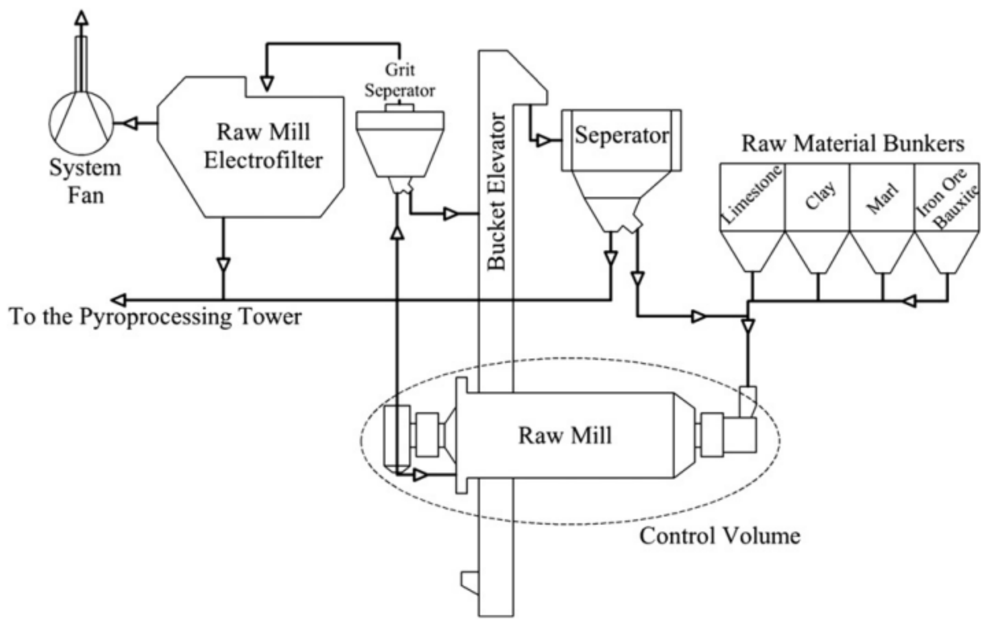


Figure 7 A typical flow diagram of the end discharge ball mill [40]

As seen in Figure 8, most contemporary cement plants are built using vertical roller mills. The roller mill's modular architecture, which includes four to six grinding rollers, enables mill operation to continue even if one roller module is unavailable due to dependability problems. Its inexpensive manufacturing and operating costs and straightforward construction are its advantages. Although vertical roller mills come in a variety of designs, they all function similarly. Each of these configurations includes a roller, or the corresponding roller grinding components, that moves along the disc's track at the level of circular movement applied by an external grinding roller. This vertical pressure on the disc is caused by the combined action of compression and shear on the material, which crushes it.

Material is ground using a motor driven by a reducer that rotates a drive disc. The material falls out of the mill through the central entrance and exit and is crushed and ground out by the roller because of centrifugal force acting on the disc edge. The material is then fed into a vertical mill with a separator, where it is reground after the separator returns the meal to the mill. The powder is ground out using air, and products are collected by dust collection equipment in the system.

Figure 8 View of grinding plant (left side) and modular vertical mill with four rollers (right side [41]

A higher air flow rate that may utilize gas waste heat while simultaneously facilitating dry grinding operations is established by the mill in the pneumatic material conveyance process. Attrition and compression techniques are used in the grinding process for these mills. The material stretched over the spinning grinding table receives the grinding action through the sets of rollers. This leads to attrition at first, then compression from outside grinding forces. In the process of producing cement, grinding parts in a variety of shapes such as cylinders, cones, balls, etc. as well as flat, curved, convex round noodles are used as roller surfaces applied to the grinding roller. These surfaces perform roller grinding near the material strength of a hydraulic system, spring pressure, etc.

2.1.3 Preheating and Kiln

Pyroprocessing is an essential step in the production of cement. A rotary kiln, a long cylindrical rotary furnace that rotates at 4 revolutions per minute, is used to create cement clinker. The production method affects the temperature range of 1400 to 1600 degrees Celsius as well as energy consumption [42]. The uniform raw meal material from the blending silo is transported to the kiln preheat tower before it then is transported to the rotary kiln, where it is fed through multiple-stage cyclones. Hot gases are used in kiln preheater towers to heat the kiln input material. The movement of materials and gases in the preheat tower is regulated by cyclones or stages. Material encounters a temperature differential as it moves down the tower, eventually reaching kiln temperature at the bottom. Refractory is used to line the tubes and cyclones to prevent accumulation, alkali attack, and abrasion from these high temperatures. Before the material is fed into the rotary kiln, the material is pre-calcined at the preheat tower. Calcination is a method of removing impurities or volatile compounds from solids by heating them to high temperatures without the presence of air or oxygen, unlike combustion, which needs oxygen. The rotary kiln receives the material from the preheat tower, where it undergoes additional calcination to produce clinker. After passing through a cooler aeration system to cool down, the hot clinker is sent to a clinker silo for storage via pan conveyors. The process of milling produces fine coal, which is burned to give heat. Heat management, airflow, emission control, dust control, and raw meal material quality are essential components of this system. Keep in mind that this is a highly condensed summary of the Union Bridge Plant's process. The route taken by gasses from the manufacturing facility and the methods used to manage the environment before releasing them is crucial to the process flow. Additionally, a wide variety of instruments are available for measuring environmental and process factors, such as gas emissions. Clinker is made in a revolving kiln and utilized to make Portland cement [43]. This apparatus consists of a big cylinder that rotates on its axis once every one to two minutes. The burner is located at the inclination of this axis at its lower end. The raw material is fed into the kiln after precalcination. The feed is fed at the top of a preheat tower, which spins, and hot gases flow upward and gently descend into the kiln. The general layout of a rotating kiln is shown in Figure 9 [44].

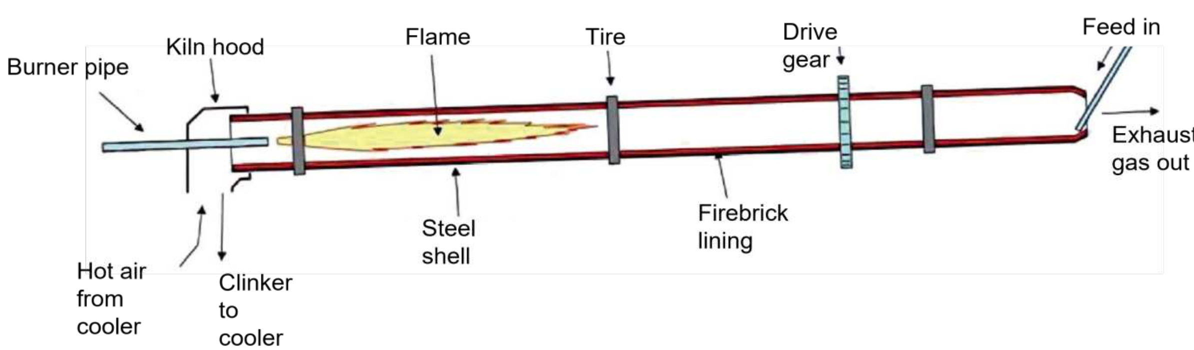


Figure 9 The rotary kiln's general design [44].

When the feed is at the proper size and composition, it is moved to the preheater, which is the initial stage of the pyro-processing unit. Here, the raw materials are preheated using a series of countercurrent flue gases from the calciner. During preheating, limestone and magnesium carbonate break down at a temperature of around 550 °C, releasing CO_2, MgO, and $CaCO_3$. At this point, the preheat tower's precalcination process starts. The precalciner is where limestone's ($CaCO_3$) chemical breakdown into lime (CaO) and carbon dioxide ($CaCO_3 \nLeftrightarrow CaO + CO_2$) starts. The physical and chemical reactions that go into creating cement are listed in Table 4. Roughly 90% of the raw feed is calcined by the preheat tower unit. The precalciner system spreads and suspends raw grain cement in airflow while producing direct combustion through solid-gas heat exchange. Before entering the kiln, the previously heated materials move to increase the temperature even higher using the calciner. The leftover calcination is applied to the precalcined meal in the rotating kiln. These reactions proceed in the calciner before being finished at 960°C in the kiln [45]. The kiln not only produces cement but also aids in many other physical and chemical processes. In most contemporary cement manufacturing plants, precalciner equipment is positioned between the rotary kiln and the preheater. Clinker is the term for the kiln's finished product. The hard, nodular material that remains after the product from the kiln cools down is referred to as clinker in the cement business. One of the components of clinker, C_2S, is formed between 900 and 1200°C, while other components, such as C_3S, C_3A, and C_4AF, are produced in the kiln during the various reaction stages between 1200 and 1280°C [33]. At temperatures higher than 1280°C, solid clinker eventually melts to form a well-mixed, nodular clinker [45].

Table 4 The list of physical and chemical reactions involved in making cement

Reaction Name	Temperature Range (°C)	Reaction	Heat of Reaction (ΔH_R)	Location Take Place
Decalcination	550–960	$CaCO_3 \rightarrow CaO + CO_2$	+179.4 kJ mol^{-1}	Preheater, calciner, kiln
$MgCO_3$ dissociation	550–960	$MgCO_3 \rightarrow MgO + CO_2$	+117.61 kJ mol^{-1}	Preheater calciner, kiln
β-C_2S formation	900–1200	$2CaO + SiO_2 \rightarrow \beta\text{-}C_2S$	−127.6 kJ mol^{-1}	kiln
C_3S formation	1200–1280	$\beta\text{-}C_2S + CaO \rightarrow C_3S$	+16 kJ mol^{-1}	kiln
C_3A formation	1200–1280	$3CaO + Al_2O_3 \rightarrow C_3A$	+21.8 kJ mol^{-1}	kiln
C_4AF formation	1200–1280	$4CaO + Al_2O_3 + Fe_2O_3 \rightarrow C_4AF$	−41.31 kJ mol^{-1}	kiln
Liquid clinker formation	>1280	$Clinker_{sol} \rightarrow Clinker_{liq}$	+600 kJ kg^{-1}	kiln

The clinker is moved to the final unit for grinding and mixing after being cooled over the cooler stage with outside air from 1450 °C to 100 °C. The calciner and kiln use the heated air from the coolers, and any leftover air is released into the sky. In addition to providing some of the kiln's needed heat energy, the heated air stream serves as a source of air for combustion. The hot air stream from the coolers and kiln exhaust is then sent into the calciner. Both streams provide air for combustion as well as heat for the breakdown of magnesium carbonate and limestone [46]. A methodical flow diagram of the cement manufacturing process is shown in Figure 10. The primary source of heat loss in the process is the preheater stage, which uses calciner exhaust to heat input materials. The pyro-processing unit, which consists of the preheater, calciner, kiln, and cooler operations, is the central component of the cement manufacturing process [47]. It is estimated that this unit consumes around 90% of the energy needed to produce cement. The endothermic process of the uncooked meal's carbonate breakdown occurs in tandem with the exothermic activity of fuel burning in the precalciner. Energy is saved and emissions from the rotary kiln and precalciner are decreased when the precalciner is operating at peak efficiency. Among the variables influencing the precalciner's efficiency is the temperature within the calciner, how long the raw meal is left in the system, solid gas separation, the effect of dust circulation, and the raw materials' kinetic behavior [48]. The final clinker quality, the efficiency of the rotary kiln operation that follows, and the energy usage of the pyro-processing unit are all directly impacted by the stability and efficacy of the calcination process.

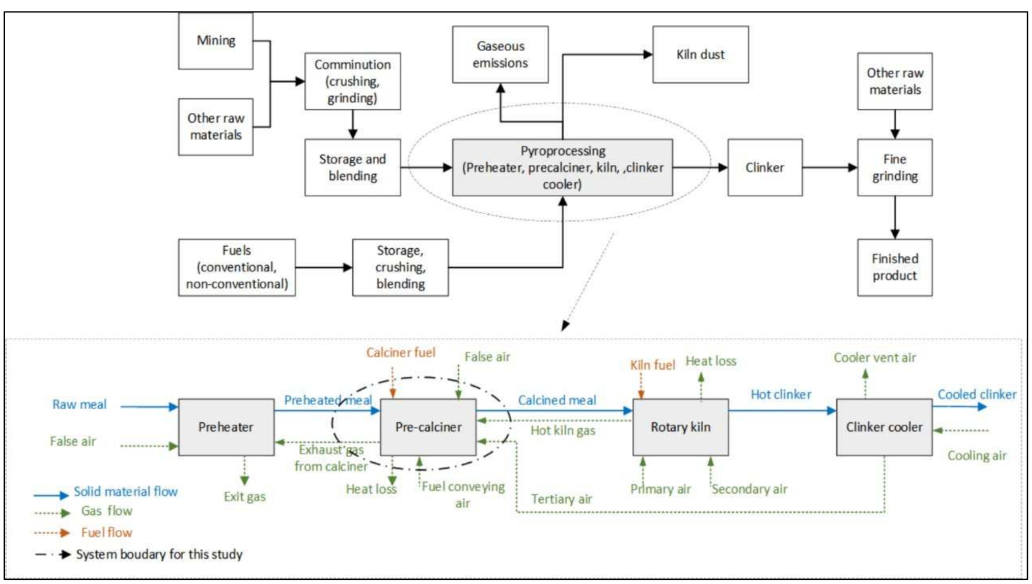


Figure 10Flow stream input/output information is shown in a schematic representation of a typical cement production facility for the pyro-processing phase [49].

2.1.4 The main phases in cement clinker

As mentioned hereinbelow, the pyro-processing of the raw meal (sometimes called the raw mix) results in the formation of clinker. The process of calcination during the pry-processing results in the formation of a clinker. Understanding the different chemical phases of the clinker helps to better understand how the calcination process works. Four minerals make up the cement clinker: tricalcium aluminate (Ca_3Al2O_6); calcium aluminoferrite ($Ca_2(Al,Fe)_2O_5$); and two calcium silicates, alite (Ca_3SiO_5) and belite (Ca_2SiO_4) [50]. Clays and limestone are heated to high temperatures to form these primary mineral phases. Clinker's four primary constituents are:

1. Alite: tricalcium silicate, which makes up roughly 65% of the whole.
2. Belite: approximately 15% of the total, or dicalcium silicate.
3. Aluminate: roughly speaking, tricalcium aluminate (usually around 7% of the whole)
4. Ferrite: essentially tetracalcium aluminoferrite, usually comprising roughly 8% of the total.

Day, Shepherd, and Wright calculated the CaO-SiO_2 (C-S) system's phase diagram (on the right) for the first time with accuracy in 1906. This demonstrates that the calcium silicates CS, C_3S_2, C_2S, and C_3S are the four stoichiometrically different forms (each with several polymorphs) as shown in Figure 11. C_2S and C_3S combinations are present in Portland cement. The shaded area in Figure 11 is where Portland cements are found.

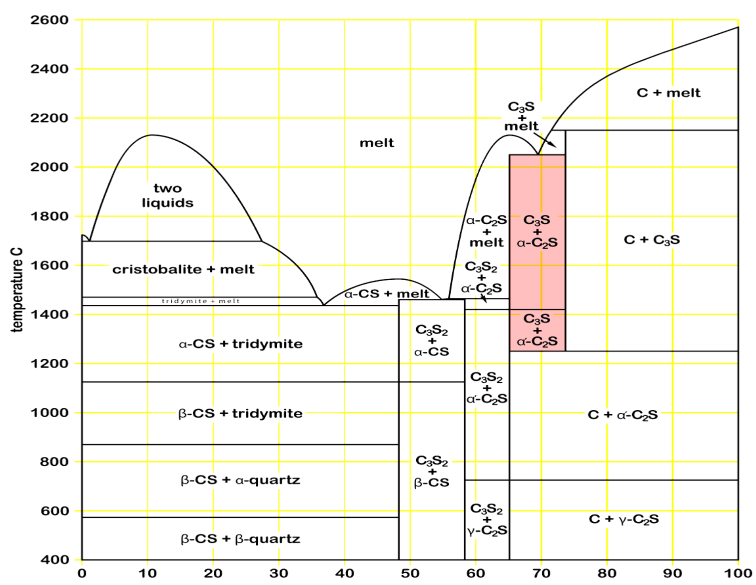


Figure 11 The phase diagram of the CaO-SiO_2 (C-S) system shows shaded areas for clinker [50].

The earliest producers of cement were unaware of this; all they knew was that some raw mix ratios of limestone to clay made good cement, while others didn't. If they performed any chemistry at all, they just measured the raw mixes' calcium carbonate content to regulate their composition. It is useful to think about mixtures that simply contain silica and calcium carbonate to simplify the understanding of the system. A combination of calcium silicates can be produced by reacting this mixture with a few mineralogical tricks.

2.1.4.1 Alite

Moore [50] noted the primary mineral (>50%) in most of the contemporary clinker is alite, which also serves as Portland cement's defining mineral. Alite cannot form unless the burning temperature rises over 1250°C, as that is the only temperature at which it becomes stable. Alite was therefore not developed in early cement that was burned at a lower temperature unless it happened by accident, and it was William Aspdin who created "Portland cement as we know it" in the first place. Under a microscope, it looked exactly like the mineral found in "grappiers" unslakeable silicate nodules in overburned lime, and Le Châtelier was the first to identify it as the main phase in clinker and assume it was tricalcium silicate because there were so few other species present that a bulk chemical analysis was enough to determine its $CaO:SiO_2$ ratio (nearly 3). Moore [50] went on to mention that hexagonal crystals are characteristic of alite formations. Nine oxide ions, nine orthosilicate ions, and twenty-seven calcium ions make up the crystal unit cell of pure tricalcium silicate. Its strong reactivity, conferred by the oxide ions in its structure, leads to the development of "early strength" (i.e., strength created in mortar or concrete during the first seven days). Although its hydration is complicated, the following equation serves as a rough representation:

$$2\ Ca3SiO_5 + 6\ H_2O \rightarrow Ca_3Si_2O_4(OH)_6 + 3\ Ca(OH)_2$$

The variable composition hydrate is commonly referred to as calcium silicate hydrate (C-S-H). As was already established, all the polymorphic variations of alite are unstable below 1250°C, breaking down into dicalcium silicate and calcium oxide. In actuality, the alite is maintained as a meta-stable phase down to room temperature, given the presence of tiny additions of other elements and quick cooling from the peak temperature. Its reactivity is partly attributed to its meta-stable nature. Alite exhibits rapid reactivity with water and primarily contributes to the initial strength development of concretes by firing a calcium carbonate source such as limestone with siliceous clays and/or shales containing oxides of aluminum and iron at temperatures of ≈1450°C; the high temperature is required to produce alite [51].

2.1.4.2 Belite

Moore [50] shows that low temperatures can be used to create dicalcium silicate, and beyond around 820°C, its "hydraulic" forms are those that react and solidify with water form. It was the ingredient that gave early cement its strength. Under a microscope, belite crystals appear as globular masses and lack well-formed angular surfaces. Eight calcium ions and four orthosilicate ions make up the crystal unit cell. Compared to alite, belite reacts with water far more slowly, usually barely half reacting after a month. Its hydration, which is likewise complicated, is generally approximated by the following equation:

$$2\ Ca_2SiO_4 + 4\ H_2O \rightarrow Ca_3Si_2O_4(OH)_6 + Ca(OH)_2$$

Moore [50] gives a detailed description of Ferrite herein. The hydrate that is generated by alite is nearly identical. The byproduct of both processes is calcium hydroxide. The "ultimate strength" of the alite paste, which is its strength after an endless curing period, is lower than that of the belite paste because it is more diluted by calcium hydroxide, which creates no strength. The alkaline conditions caused by the calcium hydroxide in the mortar or concrete are advantageous for reinforced concrete because they stop steel from corroding. When silica (SiO2) and calcium carbonate (CaCO3) are combined in molar ratios of 2:1 to 3:1, crushed extremely finely, and then heated to 1400°C, a mixture of alite and belite is formed; the proportion of each depends on the original mixture's composition. Mixtures with molar ratios greater than 3:1 will result in a mixture of free calcium oxide and alite since there is no calcium silicate with a higher calcium concentration than alite. A mixture of belite and lower, non-hydraulic silicates, like rankinite, occurs if the molar ratio is less than 2:1. This procedure shows how the composition of the raw mix can be used to regulate the composition of the clinker, albeit the actual problem is considerably more complicated because the mix contains so many more ingredients. It also serves as an example of how sensitive the system is to even slight variations in the composition of the raw mix. Calcium carbonate makes up 76.91% by mass of the combination used to generate pure belite, compared to 83.33% in the mixture used to make pure alite. Thus, a 6.4% change in the rawmix composition results in a complete transformation of the product. Belite is polymorphic as well. The low-temperature form of γ-dicalcium silicate is distinct from the others due to its non-hydraulic nature. Since it is lime olivine, its structure is entirely different from that of belite, and the total atomic rearrangement required to convert the β-to-γ-form causes the crystal to crumble. In the early industry, this "dusting" was a frequently seen (and feared) procedure. Usually, the breakdown of the belite triggered the simultaneous breakdown of the alite, rendering the resultant dust ineffective. Like alite, the high-temperature forms are maintained as meta-stable phases at ambient temperature through quick cooling and "doping" the silicate with "foreign" atoms. In contemporary kiln systems, this is easily accomplished, but in a bottle kiln, for instance, it was challenging to produce adequate cooling.

2.1.4.3 Aluminate

Moore [50] shows that in general, $Ca_3Al_2O_6$. Though early cement may have contained mayenite (approximately $Ca_6Al_7O_{16}.OH$), this calcium aluminate mineral has the greatest calcium content of all the minerals and is the only one that is typically present in Portland clinker. Its crystals grow as an interstitial phase to fill up the spaces between the silicate crystals that are available. There are multiple stable polymorphs across the whole temperature range; the dominant polymorph is determined by the number of minor elements, especially alkalis, that enter the structure. There is just one crystal form for pure tricalcium aluminate, which is a cubic structure with eight ring-shaped $Al_6O_{18}^{18}$- ions and 72 calcium ions in each unit cell. Because the structure contains many open cation sites, two alkali metal ions can take the place of a calcium ion to accommodate alkali.

Moore [50] gives a detailed description of Ferrite herein. The molecule $NaCa_4Al_3O_9$ (n=0.33, Na2O 7.6%) and its potassium equivalent, which are frequently cited, are legendary. But there are always a lot of additional ingredients in cement in addition to tricalcium aluminate. Specifically, more cations may be accommodated in the aluminate structure due to the replacement of silicon, and the values of n for the isomorphs in the table are all significantly greater in real-world aluminate phases. Good manufacturing practice avoids producing the orthorhombic and monoclinic forms of tricalcium aluminate because of their increased reactivity with water, which is expected given their higher basicity. This makes the setting of cement more difficult to control. Usually, this is achieved by making sure that the clinker contains enough sulfate to tie up the alkalis in salt phases. Tricalcium aluminate reacts quickly and exothermically with water in the absence of sulfate to create hydrogarnet:

$$Ca_3Al_2O_6 + 6H_2O \rightarrow Ca_3(Al(OH)_6)_2 \text{ Hydrogarnet}$$

As a result, when cement is created by grinding clinker without adding gypsum, a phenomenon known as "flash set" occurs. After adding water, the cement/water mixture sets in a matter of minutes. Gypsum, or more accurately, bassanite, which is a slowly soluble sulfate, can be added to change the hydration reaction by providing a high enough concentration of sulfate ions.

$$Ca_3Al_2O_6 + 3CaSO_4 + 32H_2O \rightarrow [Ca_3(Al(OH)_6).12H_2O]_2.(SO_4)_3.2H_2O \text{ Ettringite}$$

The tricalcium aluminate crystal is "passivated" when the extremely insoluble ettringite develops a thin, cohesive, waterproof film over its surface, halting further reaction. This means that the ultimate hydration of the aluminate is postponed until an hour or two after the alite has experienced its considerably slower setting reaction. Naturally, this wait is essential to using cement effectively since the paste needs to be liquid until the mortar or concrete is applied. The slow transformation of the ettringite into "monosulfate," or a "AFm" phase, is the last reaction of the aluminate;

$$[Ca_3(Al(OH)_6).12H_2O]_2.(SO_4)_3.2H_2O + 2\ Ca_3Al_2O_6 + 4H_2O \rightarrow 3\ [Ca_4(Al(OH)_6)2.(SO_4).6H_2O] \text{ "monosulfate"}$$

This annoying behavior can only be attributed to the tricalcium aluminate. Even without sulfate, cement without tricalcium aluminate sets normally. Moreover, the strength of the cement is not greatly impacted by the aluminate's eventual hydration. Overall, tricalcium aluminate can lead to serious issues and adds next to nothing to the qualities of cement.

2.1.4.4 Ferrite

Moore [50] shows that this phase's makeup varies the most out of all of them. Its changing aluminum/iron ratio is accompanied by a high capacity for "foreign" element uptake. It serves as the system's "garbage can". According to Taylor, ferrite in clinkers with greater alumina concentrations has the following "typical" composition:

$$K_{0.01}Na_{0.01}Ca_{1.98}Mg_{0.17}Ti_{0.05}Mn_{0.02}Fe_{0.62}Al_{1.00}Si_{0.14}O_{5.00}$$

and for ferrite in clinkers containing lower levels of alumina:

$$K_{0.01}Ca_{1.98}Mg_{0.17}Ti_{0.05}Mn_{0.02}Fe_{0.90}Al_{0.72}Si_{0.14}O_{5.00}$$

Moore [50] gives a detailed description of Ferrite herein. Once more, the quantity of each "foreign" ion is determined by the quantity of that element in the bulk composition. Ti-Zn transition metals are a convenient iron alternative, and they primarily end up in the "ferrite" phase of clinker. These metals in the "ferrite" of white clinkers, especially titanium, may be more prevalent than iron. It is also possible to replace Fe_3^+ with Mg_2^+, balancing the charges by replacing an AlO_4^5- ion with a SiO_4^{4-} ion. This gives MgO a place to live above the 1.5% that alite and belite can hold, while clinkers containing more than 3% MgO will always have the free oxide (periclase) as a distinct phase. Brown millerite, the "pure" mineral in the absence of other elements, is composed of a very broad solid solution series with the formula $Ca_2Al_2nFe_2$-$2nO_5$, where n=0 to 0.7. Orthorhombic crystals are present. The aluminum-to-iron ratio of the clinker determines the composition that is formed; nevertheless, cooling speeds and the presence of minor elements also play a role. Like tricalcium aluminate, the ferrite hydrates to form hydrogarnet.

$$Ca_4Al_2Fe_2O_{10} + 7H_2O \rightarrow Ca_3(Al(OH)_6)_2 + Fe_2O_3 + Ca(OH)_2$$

Ferrite is "self-passivating" in this instance because it precipitates insoluble iron oxide on the crystal surface, shielding it from additional reactions. Thus, while ferrite hydrates with a substantial amount of energy, it does not flash set and is therefore less hazardous than tricalcium aluminate. It acts as a diluent alone, adding no strength and simply changing the qualities of cement strength. It matters that almost all the transition metal ions in the clinker end up in the ferrite, which is a significant feature. The ferrite, which gives the clinker its overall color, has a dark greenish-grey color while the other phases are almost colorless. This is the reason that limiting the amount of transition metals in the raw mix helps to reduce the amount of ferrite in white clinker.

2.1.4.5 Finish grinding of Clinker

Before being delivered to the blending and grinding mills, the hot clinker is cooled using electrical fans. Clinker grinding is the final stage of the cement production process. Here, the clinker is ground into a powder and combined with other ingredients. The precise types, amounts, and compositions of additives applied to the powdered clinker vary depending on the cement market, cement standards, and availability of the additives. The clinker factor (CF), or the percentage of clinker in cement, is a crucial component from both a technical and business standpoint.

2.2 Digitization in Cement Manufacturing Plant

Although the cement industry has grown throughout time, there are still several challenges that could lead to further development. The transition from wet to dry kilns in cement manufacturing over time has significantly affected output. Despite these advancements, the cement industry still faces substantial challenges from social, political, environmental, and sustainability issues [13]. This industry, which competes in a highly competitive global business environment, is searching for ways to reduce manufacturing costs without compromising product yield and quality. Only recently has there been a shift toward digitization and predictive analytics, propelling early adopters to new heights of performance. Digitization has also helped other businesses lessen their environmental effect through operational optimization. Organizations need to work toward a digital transformation and adjust to the ever-evolving digital landscape. Several manufacturing industries have already benefited from digitization by putting solutions into practice [52]. By doing the same, the cement and aggregate industries will be better equipped to manage the substantial energy requirements, rising costs, inefficient use of raw materials, transportation problems, emissions, and overall process complexity that are inherent in their day-to-day operations. This portion of the chapter presents the findings from a review and analysis of the literature as well as the challenges facing the cement industry while applying digitization and artificial intelligence (AI). It also discusses the benefits for some cement-making plants that successfully implement digitization adaptation, like Heidelberg Materials, and how the research project used past production performance data.

2.2.1 Analysis of Digitization and predictive analytics in cement

The idea of digital transformation, sometimes referred to as digitization or digital business transformation, is the deliberate application of digital technologies to expedite and simplify an operating process. It explains how to create an electronic replica of a "real world" object or event so that it may be shared across networks and stored, viewed, and altered on a computer [53]. Predictive analytics is another aspect of digitization that uses organizational data streams to inform operational choices.

Gaining access to the various advantages of digital transformation is the aim of digitization. As demonstrated by the usage of digital twins in additive manufacturing, many businesses are starting to leverage digital technology to supplement the constraints of the physical world today [54]. They can reach the proper clients and launch their products into the market more quickly thanks to innovative developments in this industry, all the while providing a flawless user experience. Companies are always adjusting to handle the constant flow of data, putting strategic business plans into place to make sure they stay ahead of the curve. The Internet of Things (IoT) and information and communication technology (ICT) are significantly more common than they formerly were, which makes digitization simple and makes use of predictive and cloud-based analytics. Businesses are utilizing the increasing ubiquity of ICT connectivity to enhance their digitalization and predictive analytics capabilities. Without making any changes to the process itself, industries are converting their analog processes to digital ones. Among the other advantages of digitization are:

1. **Access:** Digitized content provides the advantage of search over print.
2. **Preservation:** Digital information does not depend on having a permanent object kept under guard, but multiple copies can be made, presuming at least one of them survives.
3. **Controls:** The digital process allows for historic process data generation and real-time analysis. Therefore, immediate decisions can be made, especially when using dashboards, and process controls can be better managed.
4. **Automation**: This helps reduce human-machine interface errors.
5. **Reduce the cost of handling:** Digitization reduces the cost of handling, storing, and duplication paper documents and in some cases can reproduce lost documents.
6. **Organization and dissemination:** Digital or electronic images can be indexed and stored in a document retrieval system easily.
7. **Simulation:** Different scenarios for a process can be tested, often probabilistically, to explore possible outcomes.
8. **Digital twins:** These are digital representations of manufacturing system components, processes, and systems that can undergo simulation.

There are a few prerequisites for applying digitization to a manufacturing process. These were noted by Bandi et al. [53], who noted some of the basic prerequisites for setting up digitization and predictive analytics. These 4 M's depicted in Figure 12 are (1) Materials (2) Money (3) Machines and (4) Manpower, and these provide the foundation for digitization. Materials include the content or output required. Money is required for any operational process. The machines consist of hardware, which includes the system, scanner, sensors, instruments, IoT configuration, ICT configuration, and software. Given the budget and schedule constraints, skilled labor or manpower is essential to the accomplishment of the project. Money is a fundamental requirement for both digitalization and predictive analytics, as they involve significant capital expenditures for the acquisition of equipment, supplies, and the remuneration of trained labor. Furthermore, some industries find it challenging to adjust to a digitalized production process due to the complexity of the technologies needed and the trained manpower required to handle these systems.

Despite the many advantages of digitization and predictive analytics, few publications on its application to cement manufacturing could be found. Only twelve highly relevant papers were found in the past 50 years on this topic; less than what might be expected even when considering that digitization is a relatively new development.

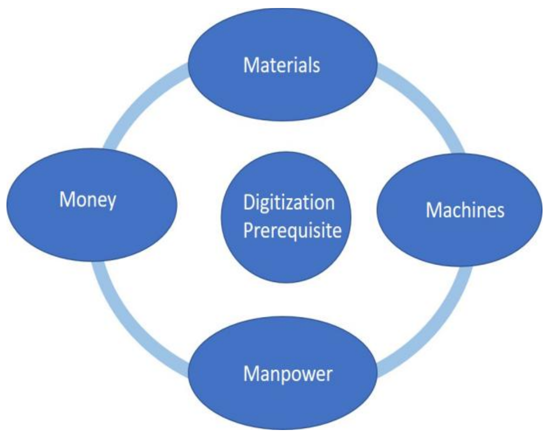


Figure 12The simplified prerequisites for digitization setup [53].

The cement industry acknowledged the value of computer control in 1970 [55] and a decade or so later, some of the first reports on digital quality control for cement kilns were published [56]. Similar publications on automated cement plant quality control were written twenty years after the first publication [57, 58]. In 2011, Stadler et al [59] discussed predictive control of cement kilns, while Mahdavi et al. [60] reported the first intelligent multi-agent system for tracking and managing the quality of cement production processes. A review paper on cement technology advancements, specifically quality control, and optimization, was produced because of this effort in 2014 [61]. Sustainability has gained importance in recent years; Mikulcic et al. [62] acknowledged this in a work on calcination and numerical simulation as an effective way to enhance sustainability. Qiao and Chai [63] also published an intelligence-based temperature switching control for cement raw grain calcination in that same year. For the rotary kiln, an internet-based fuzzy control system was reported in 2017 [64]. Nonetheless, it appears that these advancements have not spread quickly across the business, and current research is focused on figuring out why. When it comes to implementing more sustainable technology, Luo et al. [65] offered a behavioral viewpoint for sustainable production at 200 cement manufacturing enterprises, demonstrating that there is frequently a significant gap between intention and execution. Anh et al. [66] examined factors influencing the effectiveness of internal control at cement manufacturing companies through a survey of 210 cement managers and employees.

The discrepancy between the acknowledgment of digitization's significance and the industry's actual adoption of it is concerning since the production of cement and aggregate involves many moving parts, machinery, raw materials, and personnel, all of which are challenging to monitor in a reliable and less error-prone way in the absence of digitization. Consumers anticipate sustainability, less of an impact on the environment, better delivery times, and quality. Adopting digitization is necessary to comprehend the performance of all assets and operations at a cement or aggregate-producing plant. In an ideal world, instrumentation and sensors would be placed alongside assets to assess performance by translating analog to digital data. After that, these digital data can be kept monitoring performance patterns in real-time, upon which judgments can be made. On top of the historical data that is gathered and preserved through digitalization, predictive analytics can be created. This is strongly tied to the goal of business analytics, which is to empower organizations to generate value through faster, better, and more informed decision-making. Since predictive analytics is less widespread in the cement and aggregate industries than it is in other industries, business analytics will be further investigated. To direct choices and actions to the appropriate stakeholders, business analytics encompasses the broad utilization of data obtained from many sources, statistical and quantitative analysis, explanatory and predictive models, and fact-based management [67,68]. Business analytics uses techniques from the information systems, machine learning, data science, and operational research domains to do this [69]. In this way, models that can offer insightful information and help with business performance decisions are included in the scope of business analytics, in addition to descriptive models.

To give businesses a competitive edge, business analytics has developed beyond basic raw data analysis on big datasets [70,71]. Given its benefits, the adoption of digital tools and predictive modeling in the business world of the twenty-first century cannot be understated. According to various scholars [72-74] business analytics can be divided into two stages: (i) descriptive analytics, which addresses the questions "What has happened?" and "Why did it happen?" as well as "What is happening now?" (Primarily in a streaming context); and (ii) predictive analytics, which addresses the questions "What will happen?" and "Why will it happen?" in the future. Most of the time, the cement industry uses descriptive analytics based on historical data, which, if digitization is used, is recorded in real-time. Trends in process conditions and asset conditions can then be evaluated. Decisions can then be made to change the process and conditions using controls. Unfortunately, descriptive analytics only give a picture of the past, therefore impacts will have already been felt.

Figure 13 presents a well-documented classification of predictive analytics solutions by Lepenioti et al. [75] that the cement and aggregate business may choose to implement. In general, these techniques fall into three groups: statistical analysis, machine learning/data mining, and probabilistic models. Each of these areas has a variety of tools.

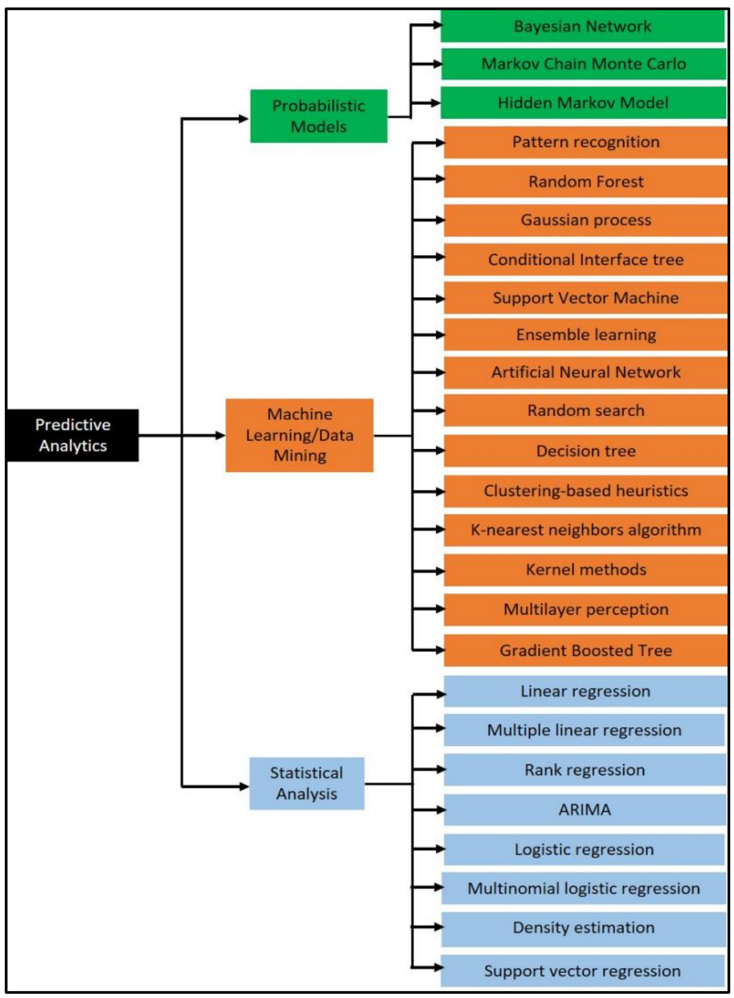


Figure 13Classification of the method for predictive analytics [75]

It is possible to modify one or more of these predictive analytics tools to assess historical data and apply the projected variable to streamline a procedure. Predictive analytic modeling is still uncommon in the cement sector, as previously indicated. The comparatively small body of research suggests that this industry is still relatively new to this kind of modeling. For the aggregate sector, predictive modeling in all operational domains of safety, dependability, productivity, raw material consumption, and emissions is limited or nonexistent due to the inability to provide historical data.

2.2.2 *Cement Manufacturing Industry Adaptation of Digitization Compared to Other Industries*

In addition to supporting automation and process management, cement makers are progressively implementing digital solutions to lower fuel use, boost output, cut emissions, and enhance product quality. A well-defined digital strategy that is in line with corporate procedures and financial objectives is essential for success. Cement manufacturers are now aiming to embrace digitalization as a vital efficiency booster. The promise of connectivity-based technologies, also known as Internet of Things (IoT) technologies, is being realized by the cement production business. In our view, it represents the union of information and operations technology, offering useful information regarding plant machinery. Cement plant managers can make better judgments on plant operations by having a solid understanding of sophisticated sensors and data analytics. To increase the amount of automation in the processes, the cement industry is constantly investing in digital assets. Systems integration, cloud computing, big data, machine learning, and artificial intelligence are a few of the new technological frontiers we are presently concentrating on. A significant component of strategic planning is the path toward digital transformation. The cement sector will greatly benefit from digitization efforts in the following areas: safety, operational excellence, controls and compliance, and culture. Most cement plants prioritize the integration of digital tools across multiple operational domains. In the upcoming years, this will not only help to create a sustainable growth journey but also to give a competitive advantage. To improve its operations and progress toward sustainability, the cement sector must rapidly develop in digitization and predictive analytics. The chemical reaction known as calcination, which happens when raw materials like limestone are heated to high temperatures, accounts for about two-thirds of those total emissions. It is essential to address this through digitalization, automation, and predictive analytics. The industry may move closer to net zero carbon emissions with the help of digitization and technology. The industry's growing emphasis on reaching energy efficiency and carbon neutrality can be met by adopting a two-pronged strategy that combines innovation and digitization. Figure 14 shows the cement industry's emission of CO2 compared to other industries.

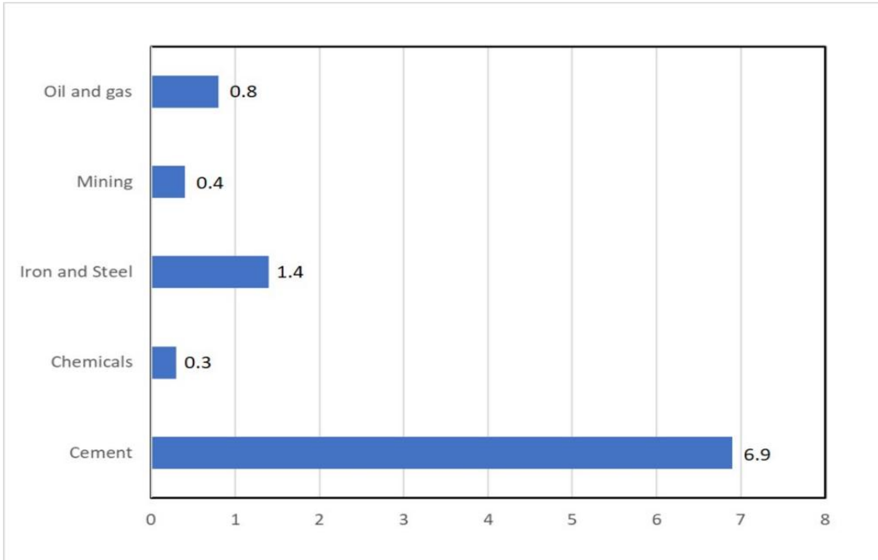


Figure 14 The share of the cement industry in global CO_2 emission [17].

Organizations that embrace technology and stay committed to digital innovation, data intelligence, and superior customer service may set the standard in a constantly changing business environment. Digitalization is being implemented slowly or not at all for the aggregate business. The logistics sector is the only indication that the aggregate industry is now seeing a digitalization trend. It is rarely observed in operations. Cement, like chemicals, iron and steel, and mining, is lagging other industries in terms of digitization and predictive analytics adoption, despite efforts to catch up. "A common definition of artificial intelligence (AI) is a system's capacity to accurately interpret external data, learn from it, and utilize those acquired insights to accomplish predetermined objectives and tasks through adaptable adjustments"[76].

Because of this, building varied AI capacities that are, system skills to accomplish certain tasks is the final component needed by industrial manufacturers to open up a world of opportunities and spur never-before-seen growth. Building data-driven AI capabilities could lead to several advantages for the development of industrial solutions, including increased productivity, better diagnostics, the discovery of more effective methods of utilization, the ability to predict how best to use resources, and dynamic and automated resource management [77-79]. The main advantage of AI is that it provides a platform for decision support by gathering insightful data and results from large, complex data sets and condensing them into a manageable format [80,81]. This gives industrial manufacturers and their clients the chance to augment and automate the solutions to pressing business issues [82, 78]. To put it another way, applying AI improves data interpretation, opening new avenues for value extraction and enabling BMI [83, 77, 84]. However, there are obstacles to overcome before AI can be fully implemented in traditional sectors. In addition to transforming their business models, skills, and partnerships, manufacturers need to intentionally build and implement AI capacity [78]. There are still large research gaps. More research is needed, specifically on the interaction between the cement industry, machine learning, and AI technological capacities.

2.2.3 Why is Digitization important for the Cement Manufacturing Industry?

In Chapter 2, we have outlined how the cement industry has delayed adopting emerging technologies like twin-digitization, machine learning, artificial intelligence (AI), and predictive modeling. Digital transformation allows manufacturing to be measured in real-time, manufacturing health data stored in a large database which can be used to perform extensive analysis to better understand how systems can be improved. Digital transformation greatly increases the speed and quality of product manufacture. Errors and delays are more likely to occur in paper-based processes. Businesses in the industrial sector may now access and utilize more data thanks to new digital developments. Companies that can analyze data more quickly and effectively than their rivals have a competitive advantage. The following are other advantages of adopting digital transformation.

- Better quality control: Digitization can help make things better, cut down on rework, and increase output quality.
- Enhanced productivity: Manufacturers can meet deadlines and complete projects more quickly with the aid of digitization.
- Lower costs: Digitization can lower waste, increase order accuracy, and optimize inventory costs.
- Enhanced efficiency: Digitization can assist boost energy efficiency and production efficiencies by up to 30%.
- Better working conditions and safety: Digitization can lead to better working conditions and safety.
- Environmental controls can be strengthened with the use of digitization.

2.2.4 Using Machine Learning and AI to Improve System Performance

A more circular and sustainable industrial sector must be adopted, and the current climate change issue puts increasing pressure on industrial producers to shoulder this obligation [85-88]. Following the logic of the twin digital transition [89] and digital servitization [90] machine learning and artificial intelligence (AI) have been portrayed as an important transformative force to address this challenge and make the industry more competitive and sustainable

[80, 83,77,91]. Many businesses that prioritize sustainability are also investing in AI development to support circular business models (CBMs), which center on generating value through the application of strategies that reduce, reuse, and recycle energy and material resources [92]. The application of predictive analytics and business analytics in general, such as predictive maintenance, has shown productivity and performance advantages across numerous industries [93]. Though machine learning and AI technologies are advancing faster than the industry can adapt, there are few real-world examples of industrial firms that can successfully create and capture sustainable value from AI-enabled CBMIs. This is because machine learning and AI technologies require the introduction of drastically different business models along with the development of new resources and capabilities [80, 78] Implementing technological capabilities of AI in practical commercial applications that bring circularity and sustainability to life has become the primary task, rather than merely developing new technologies. The industrial landscape is about to undergo an unparalleled transformation as it embraces the boundless possibilities of machine learning and AI. This revolution can unleash unrealized potential and usher in a new era of productivity and creativity for the sector. Imagine, for instance, that all underground mining operations are run by autonomous vehicles, with all energy systems and process components tuned to reach net zero. It serves as an outstanding example of artificial intelligence's potential, providing mining operations with previously unheard-of levels of efficiency, sustainability, and safety. Indeed, according to some studies [81, 90] machine learning and AI are the most sophisticated and next generation of industrial digitalization and digital services. The availability of huge data, the self-learning abilities of algorithms, and the power of computers are the driving forces behind the increasing hype and investments in industrial machine learning or AI capability [80,76]. Industrial machine learning and AI capacities, then, entail utilizing digital technology such as sensors, connectivity, and sophisticated algorithms to offer fresh opportunities for creating value and generating income [81]. These opportunities may also lead to increased profitability [90], ecosystem collaboration [94] and industrial sustainability [91]. But now, we don't know enough to define AI capabilities or how useful they are to industrial companies when it comes to enabling cutting-edge digital solutions.

The potential of AI to facilitate the development of circular business models has been emphasized in several studies [83,95,96]. For instance, by minimizing resource loop leaks, AI can help supply chains become more "circular" by facilitating increases in productivity and efficiency. AI primarily provides industrial companies with two essential functions: automation and augmentation [97,98]. By utilizing AI, augmentation can improve efficiency and human decision-making [97]. Automation also involves using AI to automate repetitive operations, increasing productivity, and cutting expenses. These two features can be used as the cornerstones for the development and commercialization of industrial CBMs, allowing businesses to devise clever solutions to maximize resource utilization, boost potential productivity, and improve their clients' overall operational efficiency [90]. More study is required to properly comprehend the potential of AI-enabled CBMs, even though there is a lot of promise in these areas. A review of the current CBM literature can offer important insights into how businesses can use AI to promote circularity. According to Chauhan et al. [83], there has been a relatively recent focus on the effects of AI on solving sustainability problems and circular economy aims.

It's time for the cement and aggregate industries to reap these same advantages, whether in pricing, logistics, predictive maintenance, or in other areas of business operations. As with any system modifications, adjustment is necessary. A more rapid and economical adoption of digitalization will be made possible by comprehensive research on digital solutions and the process expertise of cement and aggregate businesses. A consistent supply of real-time data allows machine learning algorithms to identify bottlenecks, anomalies, and other operational inefficiencies quickly. This study adopts a machine-learning methodology to predict CO_2 for cement manufacturing using historical data collected based on digitization. This shows how relevant digitization and machine learning are to the cement industry moving forward.

2.3 Impact of Cement Manufacturing on the Environment, Social and Politics

The life cycle of cement manufacturing is important and needs to be considered. The study of this research work is to adopt methodologies that can help reduce the impact of cement manufacturing on the environment, social, and politics. It contributes novel ideas in the life cycle area of cement manufacturing. Despite cement's important social significance, the production of cement hurts the environment at every step of the process. These include the release of gases and dust into the atmosphere, noise, and vibrations caused by machinery use and quarry blasting, and the permanent deformation of the surrounding landscape that might result from limestone quarries. Many cement-producing enterprises utilize equipment to limit dust emissions during quarrying and cement making. When calcium carbonate is heated to produce lime and carbon dioxide, it releases carbon dioxide into the atmosphere directly. The production of cement also releases greenhouse gases indirectly, when energy is used, especially if it comes from fossil fuels. Per tonne of clinker produced, a cement mill uses 3 - 6GJ of fuel, depending on the procedure and raw materials employed. Today, the main fuels used in most cement kilns are coal and petroleum coke, with fuel oil and natural gas being used to a lesser degree. If they fit certain requirements, certain waste and byproducts with recoverable calorific value can be utilized as fuels in a cement kiln, taking the place of some traditional fossil fuels like coal. Cement production has a great deal of both beneficial and bad effects locally. Positively, the cement sector might give locals jobs and business prospects, especially in isolated parts of developing nations where there aren't many other options for economic growth. The extraction of limestone, the raw material for cement, has detrimental effects on the surrounding biodiversity, the environment, and dust and noise pollution.

2.3.1 Environmental and Social Impact of Mining Raw Material for Cement Manufacturing

In the past, the primary goal of mining has been to maximize profits, with little regard for the environment, the local people, or development. Even outside the actual borders of individual mining leases, the extraction of minerals either metal or nonmetal has nevertheless resulted in varied degrees of social footprints due to environmental degradation, effects on human health, and social dislocation. Additionally, a substantial portion of the improved mining footprint throughout a vast geographic area is also attributed to long-distance mineral transportation and in situ beneficiation. This shows that no mining can be completely free of all negative effects, and there is enough evidence to suggest that the industries need to improve the mining sector's overall performance urgently and significantly from the perspectives of the environment and health [99,100]. The effects of mine operations on the environment and society have been a major source of worry in recent years. Mining operators and environmentalists oversee the corrective and mitigating actions. The social effects of mining operations on the local socioeconomic environment and the impacted people must be carefully considered.

As was previously noted, mining is used to obtain limestone, which is the primary ingredient in cement production. Sand, which is also mined, is the ingredient that is utilized, for instance, as the silica chemistry correction factor during cement making. These illustrate the importance of mining to the cement sector. Unfortunately, loss of natural resources and destruction of ecosystems are among the social and environmental issues brought on by mining. There are three types of environmental impacts: temporary (just during operational activities), chronic (long-term, deriving from mineral extraction and waste disposal), and transient (typically acute, connected with accidental spills or explosions). The following are the main effects of mining on the environment:

- Water accessibility and quality
- Air quality

- Land disturbance
- Waste generation
- Biodiversity loss
- Nuisance and disturbance

The social impacts are

- Housing displacements
- Resettlement
- Employment
- Health and Safety
- Ecosystem services
- Socio-political conflicts

Environmental effects frequently cause most social effects. Nonetheless, a few antagonistic and synergistic elements regulate the social effects. The use of illicit mining methods in the majority of developing nations is a growing source of worry regarding the environmental effects of mineral product exploration, extraction, and use. For instance, Bliss [15] used the phrase "sand mafia" to describe the terrible societal effects of sand mining on the environment in most third-world nations, such as India. Some of the effects of illicit sand mining on Indian rivers and coasts were also included in the article. These included: (1) biodiversity losses; (2) land declines; (3) a reduction in the ability to withstand extreme events such as river floods, coastal storms, and marine currents; (4) changes in the availability of water due to pollution and a lowering of the water table; (5) damaged infrastructure, such as embankments; and (6) changes in landforms and landscapes. The majority of poor nations still engage in this illicit sand mining today. In his study, Rege [101] made a similar observation. Such illicit operations will be impacted by finding a way to lessen the volumetric requirement for sand as an additional material for cement making. The less sand is needed as a raw material, the less sand is needed as an additive in the production of cement because of the usage of other materials. This calls for the application of system engineering techniques and cutting-edge technology. A location along the Indian coast used for illicit sand mining is depicted in Figure 15. A sand and gravel stream bed are depicted in Figure 16 (A) together with the nick point those forms after a pit is excavated, and (B) along with the upstream head cutting and downstream bed deterioration that occur during high flows [15].

Figure 15 The India Coast is home to illegal sand mining operations (Photo Source: http://static.picturk.com/syngenta-exhibition/img/works/406d631630d7a30352438b3e8ac6fa19_slider.jpg)

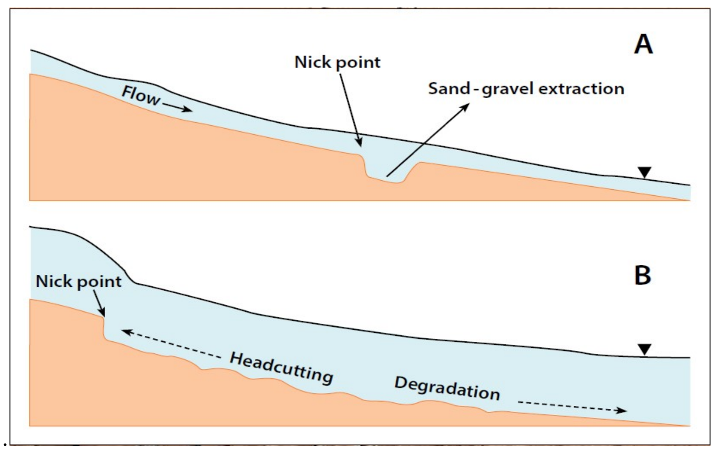


Figure 16 (A) the nick point that develops with a pit excavation, and (B) the upstream head cutting and downstream bed degradation that develop during high flows due to the impact of illegal sand mining along the coast of India (Diagram source: http://threeissues.sdsu.edu/three_issues_sandminingfacts01.html)

2.3.2 Cement Manufacturing quarry overburden waste dump impact on the environment

"Managing waste presents a significant environmental challenge worldwide, with the mineral industry emerging as the largest contributor to global waste generation" [102]. The generation of mining waste is estimated to be 50 times higher in terms of annual volume, representing immense environmental risks and liability [103]. Mining practices usually generate extensive amounts of solid waste due to the removal of overburden to expose minerals or ore which in the case of cement manufacturing is limestone. The mining sites, when analyzed individually, i.e., per enterprise, are in relatively restricted areas (on the order of tens to thousands of hectares), but the footprint required to dispose of mining waste can be very large [104]. However, even on a local scale, a substantial portion of mining waste volume is often disposed of in biodiverse areas, forest remnants, crucial habitats, and freshwater ecosystems. Studies indicate that mining activities generate impacts and represent considerable risk, specifically for sites with high concentrations of endemic species of vascular plants, cave invertebrates, anurans, and birds [105-107]. The overburden is stored in land fields called mines or waste dumps. These waste dumps erode and sometimes affect the quality of surface water. Another negative environmental impact caused by mining waste is the loss and degradation of natural areas. Furthermore, these dumps cover substantial areas that could have other uses. Regarding dump piles, there is no federal open-access database on with geotechnical risk or environmental damage potential classification, at least in the manner established by dam safety public policy [108]. Nevertheless, it is imperative to promote this discourse, especially given that certain waste piles exceed heights of 300 meters and possess individual capacities for storing tens of millions of cubic meters of waste.

Furthermore, some large dump piles are associated with a watercourse and exist in locations with average annual rainfall between 1300–2500 mm [109] for example, see Figure 17 A,B. This association reinforces the potential for environmental damage because water is the main transport agent of sediments and contaminants leached from these structures [110]. Certain materials, like sulfides, when deposited in heaps, are known for their geochemical reactivity and significant potential for environmental pollution. Even if these materials are labeled as "inert," their pollution potential remains substantial due to the vast quantities of sediments and dust generated [110]. This scenario applies even to limestone extraction for cement production, which also results in the creation of waste dumps.

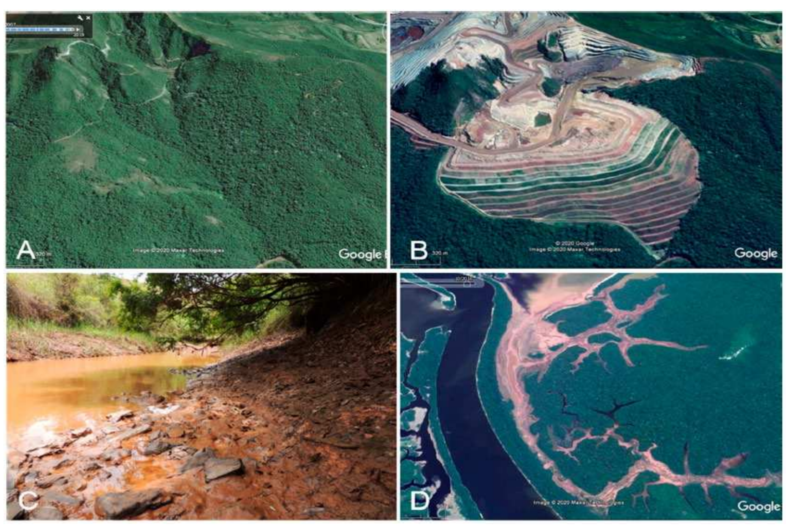


Figure 17 Freshwater ecosystems and Brazilian forests affected by mining waste. Atlantic Forest: (A,B) Pollution and silting of the watercourse downstream of mining dams and piles; (C) Loss of forest and stream due to the creation of dump piles from mountaintop iron mining (photos from 2006 and 2018, respectively). (Image: Instituto Prístino, 2019), Amazon Rainforest: (D) Bauxite mining waste discharge causes pollution and silting of the Caranã Stream (Batata Lake) [102].

The secret is to apply cutting-edge planning tools to reduce the overburden volumetric removal and to use the material as an in-situ additive alternative for other raw materials used in the cement manufacturing process. There will be less need for additives like sand and fewer big areas created for overburden garbage dumps the more natural quarry in-situ material that can be used in the raw material mix for cement. Since there would be less demand for sand, this would have a favorable effect on the illicit mining of additive materials like sand. Furthermore, waste's negative effects on the environment would decrease.

2.3.3 Cement Manufacturing CO_2 Emission and its contribution to Global Warming

Greenhouse gas emissions blanket the Earth, trapping heat from the sun, leading to climate change and global warming. Today, the Earth is experiencing warming at a pace unprecedented in recorded history. This rapid increase in temperature is causing shifts in weather patterns and disrupting the natural balance of the environment. As a result, humans and all other life forms on Earth are facing significant risks. There is a widespread consensus that global warming represents the most significant threat to both the environment and the economy in our time. According to studies conducted by [19,18], greenhouse gas (GHG) emissions linked to human activity are the primary driver of global warming, and if left unchecked and unmitigated, can have disastrous effects. The alarming level of greenhouse gas (GHG) emissions has been attained and is predicted to rise even quicker because of the rapid expansion of industry and the sharp rise in both public and private transportation. The United States Department of Energy stated that by 2015, there may have been a 50% rise in global carbon emissions over 1997 levels. If present emissions continue at their current rate, the buildup will raise the global mean temperature (GMT) to 5.8^C in the 21st century a threshold previously mentioned by [117,118].

The following are some risks that an increase in GMT could bring about: extreme weather events, large-scale discontinuities, and unique and imperiled systems.

- Risk to unique and threatened systems:

Twenty to thirty percent of all known plant and animal species would go extinct if global temperatures rose by one degree Celsius or more beyond 1990 levels. Numerous endangered systems, such as biodiversity hotspots, would also be at risk [113].

- Risk of extreme weather events:

If GMT keeps rising, some of the extreme weather events that will occur are an increase in heat waves, intense precipitation events, and the strength of tropical cyclones [114].

- Risk of large-scale discontinuity:

It is quite likely that sea level rise brought on by millennia of global warming would result in the loss of coastal lands and other consequences [115].

Because of all these predicted disastrous catastrophes, governments, and businesses have been pushed to invest resources and effort in researching, finding, and putting into practice effective ways to reduce the build-up of greenhouse gas emissions in the atmosphere. Among the United Nations Framework Convention on Climate Change's (UNFCCC) most recent international initiatives were the Kyoto Protocol and the Copenhagen Conference. Certain nations were required by these accords to cut their emissions of greenhouse gases (GHGs) to certain limits [19]. Of all the greenhouse gases (GHGs), carbon dioxide is the most significant and prevalent gas and has the largest impact on the global warming phenomena. Therefore, the primary goal of research to lessen the threat of climate change is to identify effective strategies for reducing CO_2 emissions. Owing to the massive use of fuels high in carbon and the prevalence of chemical and petrochemical products, industrialized nations account for most CO_2 emissions. In 2008, just ten countries accounted for two-thirds of the world's CO_2 emissions (19.1 Gt CO_2), with the United States and China alone contributing 12.1 Gt CO_2, or almost 41% of worldwide CO_2 emissions. In 2008, the primary sectors contributing to CO_2 emissions were transportation, industry, electricity and heat generation, and home use. Two-thirds of the world's CO_2 emissions in 2008 came from the transportation electricity and heat-producing sectors. The International Energy Agency (IEA) estimates that 41% of the world's CO_2 emissions in 2008 came from the power and heat-producing industry. The primary cause of world emissions is the burning of coal, which is the fossil fuel with the highest carbon content. The overall CO_2 emissions from the production of heat and electricity remained constant from 2007 and 2008. The amount of coal consumed increased by 4%, whereas the amount of CO_2 emitted from gas and oil increased by 3%. Transportation accounts for 22% of worldwide CO_2 emissions, making it the second largest sector. Like the power and heat generation sectors, transportation is predicted to have a significant increase in emissions in the future. According to IEA statistics from 2010, there will be a 45% rise in transport demand by 2030 compared to the current level.

According to IEA estimates from 2010, industrial processes (such as the production of electricity and heat) are responsible for over 61% of the world's CO_2 emissions. These emissions have a substantial impact on climate change. Global industrial GHG emissions are increasing quickly, and by 2030, it is predicted that there will be 14 Gt CO_2 in the atmosphere, despite the urgent need for energy and emissions reductions being acknowledged on a global scale [116]. The primary cause of this emission is the massive amounts of carbon-intensive fossil fuels that are burned to produce the necessary power. Furthermore, several industrial operations involve chemical reactions that convert raw materials into flavorful gases like CO_2. The aforementioned processes encompass the production of iron, steel, and metallurgical coke; the process of making cement; the production of ammonia; the production of lime; the use of limestone and dolomite (such as in flux stone, flue gas desulfurization, and glass manufacturing); the production and consumption of soda ash; the production of titanium dioxide; the production of phosphoric acid; the production of ferroalloy; the production of silicon carbide; the production of aluminum; the petrochemical; the production of nitric acid; and the production of lead and zinc [117]. With the United States of America being the second-largest carbon producer, the three main industrial sectors that emitted the most CO_2 in 2009 were the manufacture of steel and iron, cement, and ammonia, with respective emissions of 42.6 Tg CO_2 equivalent, 29.4 Tg CO_2 equivalent, and 11.8 Tg CO_2 equivalent [117]. Among industrial operations, the production of cement has consistently been listed as one of the major sources of carbon emissions. According to [21] cement has historically been one of the major sectors of the economy for producing CO_2 emissions. Cement factories account for about 8% of global CO_2 emissions, with each ton of cement produced releasing 900 kg of CO_2 into the atmosphere. During their inquiry, they examined international programs and possible solutions to reduce the carbon dioxide emissions of cement. Others have recently focused on creative ways to reduce the carbon footprint left by the cement industry's manufacturing process.

2.3.4 CO_2 Emission through Calcination during Cement Manufacturing Pyro-processing

The process of calcination involves using heat to remove a volatile fraction, changing the chemical composition of mineral ore. This process does not require the absence of oxygen, in contrast to pyrolysis [118]. The CO_2 emissions during cement manufacture come from four sources: Ten percent of emissions come from the transportation of raw materials, forty percent come from the combustion of fossil fuels during the calcination process, fifty percent come from the decomposition of $CaCO_3$ and $MgCO_3$, eighty percent come from the production of CaO and MgO via simple chemical reactions, and the remaining ten percent come from the electricity produced for electrical motors and facilities [119]. In addition to the above-mentioned intensive fuel use, power consumption, and fundamental chemical reactions, a host of small and big technical and managerial issues within the plant can impact plant performance and lead to an increase in fuel and energy consumption. These increased consumptions could lead to significant thermal waste and a remarkable increase in CO_2 emissions. The many sources of CO_2 in the cement-producing facility are depicted in Figure 18. Our research focuses on CO_2 produced during the calcination process during the manufacturing of clinker, as illustrated in Figure 18.

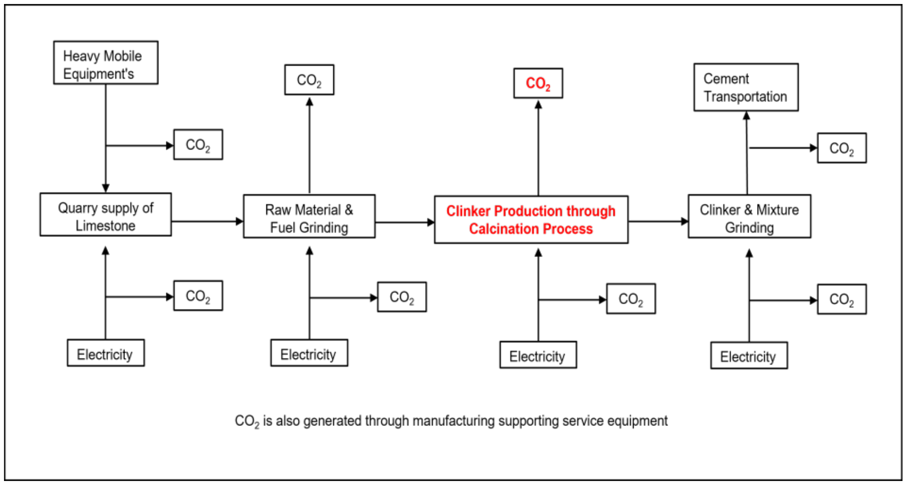


Figure 18 Simple cement manufacturing process showing the CO_2 generation systems

According to [51] carbonates break down in a highly endothermic manner. A limestone particle must undergo multiple stages of calcination, with the calcination conditions influencing the rate-determining factor at each stage. In addition to the chemical reaction that occurs at the reaction interface and involves the mass transfer of carbon dioxide from the reaction interface to the bulk gas, these processes involve heat transmission from the bulk gas to the particle's exterior surface and from the external surface to the reaction interface [120]. On the other hand, if the bulk gas temperature is high and the particles are small, the rate of heat and mass transfer will usually be high. The chemical reaction in cement manufacturing is the procedure that establishes the rate for the circumstances [51,121]. The concentration of carbon dioxide in the atmosphere would rise from roughly 25 mol% to more than 100 mol% if the calcination process was electrified. Numerous factors, including the process chemistry, heating of the raw materials, calcination, clinker generation, and ultimate cooling, may be impacted by this. As Figure 19 illustrates, the rate of calcination will be slower because of the rising partial pressure of carbon dioxide [122-126]. The feasibility of an electrified calcination step was examined by [127]. who concluded that electrical heating-based calcination appears viable and would provide equivalent process parameters without negatively affecting product quality? According to

[128], laboratory tests on Oxyfuel combustion that changed the gas phase's carbon dioxide content revealed a slight modification in the product's quality.

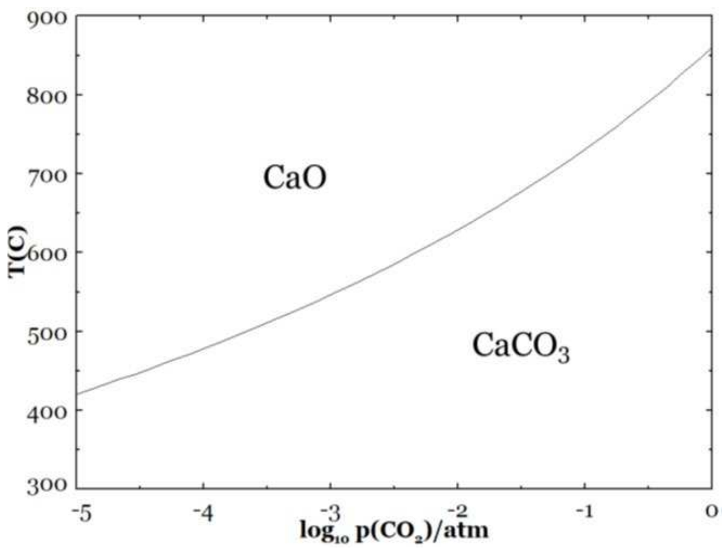


Figure 19 Calcium carbonate calcination temperature as a function of carbon dioxide partial pressures at 1 atm. Calculated with FactSage 8.o software [126,129].

In other publications over the past few decades, the kinetics and chemical mechanisms related to the calcination of carbonates have been extensively discussed [130,131] owing to its technological significance, the calcination of $CaCO_3$ [132] has received particular attention. Garcia-Labiano et al. [133] state that there are some ambiguities regarding the reaction. Reactions were offered in light of the lack of consensus over the procedure.

$$CaCO_3\ (s) \rightarrow CaO\ (s) + CO_2\ (g),\ \Delta HR = +168\ kJ/mol$$

$$CaCO_3\ (s) \leftrightarrow CaO^*\ (s) + CO_2\ (g) \leftrightarrow CaO\ (s) + CO_2\ (g)$$

$$CaCO_3\ (s) \leftrightarrow CaO\ (g) + CO_2\ (g) \leftrightarrow CaO\ (s) + CO_2\ (g)$$

Hyatt et al. [131] reported that the structure of CaO is metastable. It is believed that the unreacted $CaCO_3$ and the freshly created CaO crystal are connected by the active CaO, shown as CaO* in the reaction. Another method proposed by [134] is that, as the reaction illustrates, $CaCO_3$ will break down into gaseous CaO and CO_2 species and condense low-volatility CaO. Calcination can be divided into three stages, independent of the underlying source: heating and heat transfer to the particle surface; reaction front chemical reactions; and CO_2 transfer from the reaction front to the ambient environment. Stanmore and Gilot [130] state that the reaction is affected by the chemical composition of the limestone, the size of its particles, the composition of the surrounding gas, and the ambient temperature. The kinetic field's degree of uncertainty increases as a result.

2.3.4.1 CO2 Emission Calculation for Cement Industry and its Policies

The cement manufacturing sector must further determine the origin of its CO_2 production and how to measure it in order to manage the gas properly. Numerous techniques have been developed over time to assist the cement manufacturing sector in determining the amount of CO_2 released during the calcination process. The technique created by the Intergovernmental Panel on Climate Change (IPCC) is well-known. Regretfully, the cement industry's use of the IPCC technique to determine CO_2 emissions is dependent on precise measurements of the amount of raw material, the amount of thermal heat from the source utilized in the calcination process, and the amount of thermal energy source used. It is particularly challenging to rely on the accuracy of results obtained because the IPCC approach employs a highly intricate empirical formula to determine the amount of CO_2 created per ton of clinker produced. Because of this, most cement factories go through thorough audits numerous times a year to determine the accuracy of the data they submit to regulatory bodies. The businesses must invest time and money in this. As previously stated, the empirical technique simply accounts for the number of materials utilized in manufacturing. Other process variables that could also affect CO_2 emissions are not taken into consideration by the IPCC approach, such as fuel flow, motor drive speed, airflow speed, and material flow. The intricacy of incorporating each of these variables into an empirical calculation prevented these variables from being considered in the IPCC methodology. This makes it crucial to think about and build additional cutting-edge methods specifically for the cement sector.

A few widely accepted yet imperfect methods are commonly employed to calculate CO_2 emissions due to their simplicity. Numerous CO_2 emission estimations have been produced in previous research. The carbon footprint is one of the important measures needed to calculate CO_2 emissions. The phrase "ecological footprint," which was used to describe the total amount of carbon dioxide and other greenhouse gas emissions related to products, along their supply chains, and occasionally including their use, end-of-life recovery, and disposal, is the source of the term "carbon footprint," also known as "carbon profile"[135-138]. The first cement-related CO_2 emissions factors, including a breakdown factor for heat-processed limestone, were released by the IPCC in 1996 [139]. Furthermore, the methods and data needed to compute stationary combustion emissions in 2006 were supplied by [140]. For the sectoral approach, three tiers of techniques are offered, based on data on fuel combustion from applied combustion technologies, technology-specific emission factors, fuel statistics, and fault emission factors from national energy statistics. It is vital to accurately estimate the process-related emission factor for clinker production in conjunction with accounting methods, as the default value suggested by the IPCC may either overstate or underestimate the total emissions of the Chinese cement sector. Equation illustrates how the stoichiometric compositions of the reaction can be used to calculate this emission factor. The two main chemical reactions in calcination are $CaCO_3CaO + CO_2$ and $MgCO_3MgO + CO_2$.

$$EF_{clinker} = {}_{Content}CaO \times 44/56 + {}_{Content}MgO \times 40$$

where ${}_{Content}CaO$ and ${}_{Content}MgO$ denote the CaO and MgO contents of clinker that need to be calculated based on assessments made at the plant level. Shen et al. [139] investigated the fuel, clinker, cement, raw materials, and meals used in 289 production lines across 18 provinces in China in 2012. They determined the process emission factors, which range from 1.4% to 3.4% below the default values specified in the IPCC Guidelines, for each kind of kiln. Without specifying the proportions of CaO and MgO, Cai et al. [141] determined that the total process emission factor was set at 0.504 t CO_2/t clinker based on extensive data from 1574 cement businesses in 2013. The process-related emissions were estimated by the NDRC in 2005 and the UNFCCC in 1994 to be 411.7 Mt CO_2 and 157.8 Mt CO_2, respectively. [142,143]. The amounts of coal needed to heat the kiln were determined by altering indicated coal intensities rather than those immediately accessible in the official numbers Lui et al. [144] which leads to high variations and uncertainty in energy consumption. Lui et al. [144] presented an alternative formula for estimating CO_2 emissions from cement production facilities. The following equation is used to estimate CO_2 emissions at the unit level and for fuel-based processes:

$$E_i = P_i \times R_{k,i} \times EF_{process,k} + F_i \times EF_{combustion,k}$$

where the variables P for cement production (t), R for the clinker-to-cement ratio, F for fuel consumption (kJ), $EF_{process}$ for process-based emission factors (g/kg), and $EF_{combustion}$ for combustion-based emission factors (g/J) are substituted for the units, $_i$, and $_k$, respectively. The letters E, P, R, and F stand for clinker-to-cement ratio, unit-based emissions (kg), cement production (t), and fuel usage (kJ). Note that this study only counts the emissions that come directly from the production of cement; indirect emissions are not considered, such as those that come from the use of gasoline in power plants to create electricity and the fuel that comes from vehicles carrying materials [144].

Machine learning and artificial intelligence (AI) methods have helped us understand complex systems better in recent years. It is not difficult to implement predictive modeling, even in complicated systems such as the cement manufacturing process. The cement business has not completely embraced machine learning and artificial intelligence, despite their widespread acceptance in other domains. Most cement factories have preserved historical data over years of process performance. It is therefore a fantastic fit for machine learning.

2.3.4.2 Using Machine Learning to Predict CO_2 Emission for Cement Industry

Some of the cutting-edge methods that are changing the world and the way research is conducted are artificial intelligence (AI), machine learning (ML), real-time monitoring, and optimization strategies. As previously stated, most of the approaches discussed here are based on the empirical calculation of CO_2 emission quantity; however, Nguyen et al. [145] conducted a thorough examination of the use of machine learning techniques for high-precision CO_2 emission prediction modeling. They demonstrate the critical role machine learning algorithms play in predictive analytics across a range of areas, including the creative profiling of carbon dioxide (CO_2) emissions to get insights into CO_2 emissions. The research demonstrates the value of these algorithms in terms of accurately calculating CO_2 emissions, assessing energy sources, quantifying emissions, and enhancing prediction accuracy is invaluable. A variety of industries have demonstrated the efficacy of deep learning, artificial neural networks (ANN), and support vector machines (SVM), while the Modified Regularized Fast Orthogonal-Extreme Learning Machine (MRFO-ELM) approach optimizes predictions for coal chemical emissions.

The application of cutting-edge technology, such as machine learning (ML) and artificial intelligence (AI), to lower carbon emissions has been covered in several studies [146,147]. Yang and O'Connell [148] produced an emission projection for fuel use in air travel over five years for the Chinese aviation industry using the ARIMA technique. A case study on the application of machine learning algorithms in conjunction with an algorithm combination strategy to forecast carbon emissions by 2030 was presented by Niu et al. [149]. In a study published in 2021, Javadi et al. [150] used data from 2015 to 2019 and the RBF network model to forecast greenhouse gas emissions in the Iranian vehicle sector by 2030. In Olanrewaju et al. [151] study on the management of emissions in Canada's industrial sectors, specifically for the year 2035, they also employed the ANN algorithm to anticipate emissions. In a different study, Hamrani et al. [152] estimated N2O emissions in agriculture using a variety of machine learning (ML) methods, including RF, LSTM, SVM, and others. The prediction accuracy of the results was evaluated. Furthermore, to manage and mitigate the negative effects of air pollution, the LSTM, CNN, and KNN algorithms were applied separately and in combination [153]. It should be noted that five predicted accuracy criteria were employed to evaluate the approaches' accuracy, even though the research used ANN, SVM, and deep learning algorithms to estimate Flu-Gas emission [154].

The cement manufacturing business is not the same as the rest of the world, even though numerous researches mentioned here demonstrate how machine learning and artificial intelligence are being successfully utilized to anticipate CO_2. The reasons behind the poor adoption of AI and machine learning in the concrete, aggregate, and cement industries are demonstrated by Boakye et al. [29] There is only one paper found (search date 7 January 2024) that discusses using machine learning to forecast CO_2 based on calcination that comes up in literature searches. Regretfully, the study is based on laboratory experimental data rather than industrial performance data. In addition to these well-known empirical procedures, Gao et al. [155] presented various methods used to estimate the quantity of CO_2 emission from cement; however, this work uses machine learning to forecast CO_2 emissions using laboratory data. According to the paper, it is advised to test the models based on specific process data that depict both average and exceptional plant operating circumstances. As a result, more accurate models based on data from real plants will be created. To anticipate CO_2, the current work uses machine learning and artificial intelligence (AI) techniques to analyze historical real plant performance monitoring data from cement manufacturing. To improve understanding of CO_2 emission and forecast, this will demonstrate the necessity for the cement-producing sectors to use cutting-edge technologies.

This work focuses on estimating CO_2 in the calcination process used in cement manufacturing utilizing machine learning and artificial intelligence. This study uses sensitivity analytics with machine learning and artificial intelligence (AI) techniques to examine the effects of manufacturing independent factors that affect CO_2 generation during the calcination process of cement making. For potential future outcomes of dependent variables, a predictive analytic training model was created based on the most influential variables identified by sensitivity analytics. This will enable the prediction of future dependent variables with a high degree of probability utilizing several independent input sets of variables, the majority of which are measured throughout the production process. It will be possible to adjust the critical independent input set of variables during manufacturing to help achieve the required CO_2 output to both enhance the manufacturing processes and lower CO_2 generation by demonstrating that manufacturing variables can be used for predictive analytics relevant to CO_2 and quantify estimates.

2.3.5 Strategies and Potential to Reduce Impact of Raw Material Usage and Overburden Waste Dumps

The cement industry makes extensive use of large stockpiles for pre-homogenizing raw materials. Combining an effective control technique with a continuously running homogenization silo yields an appealing alternative to raw material mixing. The advantage of the latter technique is that it avoids the need for significant investments in homogenization equipment; however, the control system requires greater attention. There are currently a few commercial systems of this kind available. These systems typically have two primary disciplines that make up their control system structure: an optimization process and a quality control system. Reductions in overburden waste, disturbance of land, and waste from raw materials are made possible by the limestone quarry's optimization and quality control system. Computer software is typically utilized to construct this raw material mix and blend optimization. Unfortunately, because of the complexity of the criteria for the quarry cement mix, most of this commercial software is less accurate. Numerous studies have been conducted on the optimization of raw materials for cement limestone quarries. Bao et al. [156] for instance, created a novel method to ascertain the chemical composition of the quarry's raw materials. A sequential branch and cut method were used by Chatterjee et al. [157] to model production planning for limestone quarries while maintaining requirements for quantity and quality. Joshi et al. [158] provided a long-term production plan that relies on a reliable supply of raw materials in both quantity and quality. They also employed the branch-and-cut method to create a manufacturing sequence. A quarry production scheduling model was given by Asad [159] to guarantee a consistent supply of raw materials from the quarry. A mixed-integer linear programming (MILP) model was created by Asad [160] to optimize the blending of raw materials, guaranteeing the goal of cost-saving while fulfilling the necessary quality and quantity requirements. De Almeida [161] evaluated the distribution of the local factor's indices using geostatistical pictures and a joint simulation (CoDSS) and direct sequential simulation (DSS) algorithm. Though it is limited in its absorption of uncertainty, the literature offered provides some insight into the planning of cement raw material production. Multiple point statistics (MPS), a newly developed framework for spatial simulation, was employed by Jones et al. [162] to assess the high-order spatial relationship. To evaluate the volumetric and geological uncertainty that can be utilized to compute grade uncertainty and deposit-wide uncertainty, MPS employs training images. To enhance quarry operations at Crystal River, Boakye et al. [163] provided a quarry optimization strategy utilizing a block model and an internal development quarry scheduling and optimization software (QSO Expert). The primary source of raw materials for a cement mill in Theodore, Alabama, is limestone, which is barged in across the Gulf of Mexico by the undersea quarry known as Crystal River Quarry. An assessment was carried out to maximize the quarry's planning and extraction processes to enhance the functioning of the quarry. To do this, a new block model was recalculated, more exploration drilling was conducted, and the most recent version of QSO Expert software was utilized. The main effects on the economy are increased limestone reserve recovery, resource sustainability, and consequently extended quarry life. Secondarily, drainage lowers moisture content, which directly lowers limestone transportation costs because limestone is mined underwater and placed above water. Furthermore, a noteworthy decrease in electrical energy consumption, a reduction in dragline maintenance expenses, and a reduction in dragline motions within the operation all contributed to a significant reduction in operational costs. Using hierarchical simulation, Vu et al. [164] evaluated the geological uncertainty associated with cement raw materials. Using Monte Carlo simulation (MCS) and indices, Shah and Rehman [165] give a thorough overview of scenario analysis of raw materials used in cement manufacturing. Using scenario analysis, one may forecast the likelihood of the best, worst, and most probable raw material quality scenarios. On the other hand, to assess the inherent uncertainty surrounding chemical composition values and examine the implications of genuinely unforeseen events, the Monte Carlo simulation is employed. The forecasted outcomes support choices on raw mix design optimization, production scheduling, and raising the likelihood of creating the ideal plan. The data presented by Joshi et al. [166] indicates that the mine under consideration can supply the cement factory entirely for a maximum of 15 years. It was also mentioned that the mine's lifespan (85 years) was significantly extended by the addition of limestone from the nearby mine. The results also demonstrated that the suggested strategy generates 10% more profit than the production planning formulation the company is currently utilizing. The proposed approach also helps identify the ideal limestone quality to be supplied from the adjacent mine at every stage of production. These studies demonstrate that cement limestone quarries may be optimized for quality and that they can be used to decrease overburden garbage dumps and increase raw material use. Our study examines alternative approaches that maximize resources, cut waste, and improve quality by utilizing cutting-edge, revolutionary software.

2.3.6 Strategies to Achieve Net Zero for Cement Industry and how this research work fits in

Complying with internationally agreed climate change goals depends on the decarbonization of hard-to-abate industries. Due to the chemical reaction of decalcining limestone, and the high energy utilization involved in cement manufacturing, as well as its widespread production and consumption worldwide, cement and concrete manufacturing are the most challenging industries in decarbonization pathways [167]. An increasing number of research papers have focused on mitigation measures in the cement and concrete sectors to meet this strategic challenge. A comparative analysis is required to assess the true contribution of each emerging technology to reaching short- and long-term carbon neutrality goals in the cement and concrete industries, even though most current research efforts are concentrated on technological advancement in cement and concrete production. This is extremely important because it may provide industry stakeholders and policymakers with vital information that will allow them to develop more strategic frameworks and effective regulations for net-zero roadmaps. Targeted tactics like these are necessary to achieve the lofty goal of becoming carbon neutral by 2050. As a result, this section of the chapter aims to explore how our research study will add to this road map and examine the possibilities for cutting carbon emissions from new alternative technologies in the cement and concrete sectors that have been put out in several articles in the open literature. In their study,

Nehdi et al. [168] provide an extremely thorough literature evaluation on this subject. Our research contributes to these new technologies in some way. It improves CO_2 prediction through machine learning, which is essential to the use of certain of these technologies.

2.3.6.1 Alternative Clinker Technology (ACT)

Approximately 0.83 tons of carbon are released during the manufacturing of one ton of traditional clinker [169, 22]. The two main sources of carbon emissions during the manufacturing of clinker are the calcination of limestone and the burning of fossil fuels. A chemical reaction known as calcination breaks down calcium carbonate ($CaCO_3$) into calcium oxide (CaO) and carbon dioxide (CO_2), which accounts for 60–65% of the carbon emissions associated with the formation of clinker [170, 171]. Implementing alternative clinker technologies (ACT) is one viable technique to accomplish decarbonization in the cement industry for medium- to long-term strategic planning. the partial substitution of cement in the making of mortar and concrete. [172,173]. Alaloul et al. [174] examined the use of OSA as an addition in cement and geopolymer concretes in a thorough investigation. Lower organic content oil shale is usually made up of more carbonate minerals. Calcareous oil shale is a kind of oil shale that has major oxide ratios that are extremely comparable to OPC clinker [175,176]. Calcareous oil shale has the potential to replace over 76% of the raw materials needed in the production of belite cement clinker, as proven by [176]. Because belite (C_2S) can be produced at lower calcination temperatures than alite (C_3S) and has a lower CaO content, it can reduce carbon emissions by up to 10%. Additionally, this quantity of oil shale can supply enough energy to replace the traditional clinker combustion fuel during the calcination process in a rotary kiln, resulting in a further significant reduction in CO_2 emissions [176]. However, rather than focusing on the suggested technology's environmental impact, most of the research that are now available in the public domain address the technical elements of cement manufacturing. Therefore, more research concentrating on embodied carbon analysis of this kind of clinker is required in addition to the evaluation of engineering performance to better assess their scale-up potential. Nehdi et al. [177] provide an extensive literature assessment on alternate clinker technology.

In the last several years, several clinker technologies have been developed to produce cement with substantially fewer carbon emissions. Cement based on magnesium oxides obtained from magnesium carbonates (MOMC) or magnesium oxides derived from magnesium silicates (MOMS) is one intriguing technological advancement. A form of magnesium hydroxy-carbonate cement that was able to sequester a comparatively large amount of CO_2 in hydration products was patented in 2009 [178]. Even though carbon sequestration has advantages, this kind of cement cannot be categorized as low-CO_2 since the magnesium oxide (MgO) needed for it must come from naturally occurring sources that do not contain CO_2 in raw materials [179,180] Thus, basic research on the process of producing magnesium oxide (MgO) from magnesium silicate rocks in an industrial setting that is energy-efficient is crucial [181] Another non-hydraulic binder that was patented in 2016 is called Solidia cement [182]. This cement's clicker, which has a composition like OPC clinker but less $CaCO_3$ and a kiln temperature of about 1200 ˚C, allows for a 30% reduction in carbon emissions [183]. Moreover, for every 1000 kg of binder, Solidia cement's curing process may absorb 300 kg of CO_2, a process that can be accelerated at higher temperatures [171,183]. Because Ssolidia cement requires regulated carbon curing technology, it can only be used in precast concrete factories. The hydraulic binder Celitement is patented by Karlsruhe Institute of Technology and SCHWENK Zement KG [184]. A short-lived precursor of CSH is stabilized and synthesized to create this cement, which requires less energy to manufacture and emits less carbon dioxide into the atmosphere [171]. X-Clinker is a different type of hydraulic binder that Tíecnico-Lisbon and CIMPOR developed and patented [185]. This cement is based on a raw mix with 33% less $CaCO_3$, a lower C/S ratio, and 25% less processing carbon emissions than regular OPC. However, the raw mixture needs to be melted at a temperature of 1550 ◦C during the pyroprocessing step to form this type of clinker. This temperature is approximately 100 ◦C higher than the processing temperature of OPC. Therefore, technical changes to the industrial plants are needed to enable the creation of a 100% liquid phase in the clinker manufacturing process. Further technical details regarding various types of clinkers can be found in the references [185-187]. The various ACTs that have been postulated in the literature have largely distinct phase compositions. Even with the advances in clinker technology, more research is still required to completely understand the engineering performance of different kinds of cement. Life cycle assessment (LCA) of the embodied carbon emission is necessary to determine the extent to which these technologies aid in the decarbonization of the cement industry.

2.3.6.2 Alternative fuel technologies (AFTs)

Globally, the production of cement generates 563 to 831 kg CO_2/tonne clk in average CO_2 emissions. The process of calcining limestone releases about 365–560 kg CO_2/tonne clk; however, energy emission releases 168–476 kg CO_2/tonne clk [171,188,189]. The global energy consumption and CO2 emissions of the cement industry in 2016 were estimated by Chatterjee and Sui [189] to be approximately 11 EJ and 2.2 Gt, respectively. According to studies, converting cement factories to fuel sources with zero emissions could cut carbon emissions from the production of cement by 25% to 40% [191,188]. AFTs, or alternative fuel technologies, have been proposed in large numbers to reduce carbon emissions related to the energy needed in clinker manufacturing. These alternative technologies can be categorized into three primary groups.

Because of their variety of resources, alternative fuels made from biomass leftovers from both biogenic and non-biogenic processes have been widely used in the cement industry. Waste and biomass fuels were categorized by Chatterjee and Sui [189] into the following areas: agriculture, manufacturing, packaging, construction and fabrication, food processing and animal husbandry, community and home, and transportation automotive resources. Numerous studies have examined the lowest heating values (LHVs) and compositions of different waste and biomass energy types, as well as the highest inclusion level that can be achieved. Another typical waste that is utilized as an alternative fuel in the cement industry is sewage sludge. Sewage sludge can be used to make cement by co-combusting in the kiln or by combining its burned ash with Portland cement. The sewage sludge can be used to recover energy thanks to the latter technique (2016). Waste plastic and used tires are regarded as two of the easily accessible energy sources for cement manufacturing and that of plastics is 28–40 MJ/kg. As an alternate fuel for clinker manufacturing in cement kilns, several tire types with a chemical composition like that produced in fossil fuel kilns could be used. With LHVs ranging from 29 to 36 MJ/kg, industrially utilized oils and solvents are another significant energy source for the manufacturing of cement. The heating value and basic composition of waste solvent and heavy fuel oil that can be burned in a cement kiln were compared by [191].

Hydrogen's distinct qualities—such as its total storage capacity, renewability, zero emissions, adaptability, and speedy recovery make it an attractive clean alternative fuel for upcoming energy-intensive materials research and industrial processes [192]. There are two ways that the cement and hydrogen fuel sectors can work together. The first method uses the burning of H_2 to supply the thermal energy required for the creation of clinker. On the other hand, the second method uses heat recovery from cement manufacturing facilities to create hydrogen. By using thermodynamic analysis, Juangsa et al. [193] showed that the carbon-free combustion of H_2 fuel in a cement manufacturing system coupled with NH_3 dehydrogenation can cut carbon emissions by 44% when compared to a coal-based plant. El-Emam and Gabriel [194] investigated seven different energy mix scenarios in which the kiln heat was partially supplied by hydrogen fuel. Compared to cement manufacturing based on coal, they discovered that employing these hydrogen-based scenarios can result in a reduction of carbon emissions of 15.–19.6%. Several significant cement production facilities, such as Heidelberg Cement in the UK and Cemex in Spain, have conducted hydrogen fuel mix trials. Another decarbonization strategy that has been proposed in several research is the production of hydrogen in cement factories [195]. A plant design for producing hydrogen from waste gasification incorporated into a cement production facility was put forth by Weil et al. [196] They claimed that the suggested hybrid system offers several advantages, including lower manufacturing costs, the use of gasification products in place of primary fuels, and the use of fuel ash as a feedstock to produce clinker [198]. To create hydrogen, Ozturk and Dincer [197] created an integrated system that combines natural gas and waste heat recovered from cement slag. In the cement plant's waste heat recovery, they were able to attain overall energy and energy efficiencies of 55% and 22%, respectively. The results of the studies show that using hydrogen fuel is a viable way to decarbonize the cement industry. However, more techno-economic evaluations are needed in future studies to pinpoint the obstacles to technological improvement and assess the environmental effects of this approach. In their study, Nehdi et al. [168] provide an extremely thorough literature evaluation on this subject.

2.3.6.3 Alternative cement technologies (ACMTs)

The technique known as Portland Lime Cement (PLC) first appeared in the late 1980s and continued to advance progressively in the 2000s [198]. PLC is made by intergrinding clinker, gypsum, and limestone; limestone usually replaces 10–20% of the OPC clinker [198]. Higher replacement levels of up to 35% are permitted for CEM Type II/B-L PLCs under the European standard EN 197 [199]. Most of the initial research on PLCs focused on assessing the material's mechanical and durability attributes; as a result, the advantages for the environment were mostly overlooked [200,201]. In the early 2000s, PLCs began to proliferate because of the realization that blended cement had a lesser environmental impact [202,203]. According to reports, PLC emits 10% less carbon dioxide than

OPC [204]. Supplementary cementitious materials (SCMs) can further lower the clinker factor and carbon emission of PLCs [205]. However, few research publications in the public domain compare the contribution of various PLC types to the short-term decarbonization plans in the cement sector. However, substituting some of the clinker with calcined clay could further enhance PCL's environmental advantages.

When additional SCMs are used, the clinker factor in PLC production could be further decreased. A promising method for using calcined clays as an efficient SCM to partially replace clinker in cement production is limestone calcined clay cement (LC3) [206]. As a result, 700–850 °C is heated to calcine clay. Because clay has a lower calcination temperature than OPC clinker, kaolinite-containing clays can be calcined using conventional rotary kilns, flash calcination units, and roller hearth kilns [207]. A sizable portion of the OPC clinker in blended cement could be replaced by a mixture of calcined clay and limestone. To attain an engineering performance like traditional OPC, 30 percent calcined clay, 15 percent limestone, and 5 percent gypsum can typically replace half of the OPC clinker. Numerous research, have looked into the mechanical, durability, and hydration dynamics of concrete made with LC3 [208]. It has been demonstrated that LC3 can significantly lower carbon emissions from the cement sector [209]. Therefore, it is possible to cut carbon emissions by up to 25 - 40% while retaining outstanding mechanical and durability performances by substituting 50% of the clinker with calcined clay and limestone [210,211]. Typically, a variety of waste types, such as municipal, industrial, agricultural, and demolition wastes, are used to generate clinker-free hydraulic binders. These binders have the potential to mitigate environmental effects by reducing carbon emissions and encouraging the value-adding and exploitation of significant industrial wastes. In most of the early research in this area, waste materials were used in place of some of the basic ingredients used in clinker. However, some research has shown that making hydraulic binders solely from waste materials is feasible.

2.3.6.4 Carbon capture, utilization, and storage (CCUS)

Carbon capture, utilization, and storage (CCUS) is a very promising and possibly necessary long-term strategy to decarbonize the cement and concrete sectors by 2050. CCUS technology can be used in the manufacturing of cement in cement plants [215], in the production of concrete during the curing process Zhang et al. [212] and in the recycling of cement-based composites that have reached the end of their useful [213]. Only the newest CCUS technologies that are relevant to cement plants are covered in this section. The four main categories of CO_2 capturing technologies are industrial separation, post-combustion, pre-combustion, and oxyfuel combustion, according to the IPCC special report on CCUS [214]. To create hydrogen fuel, the pre-combustion CCUS methods are primarily combined with gasification technologies. However, as stated by Plaza et al. [215], direct CO_2 capture Hills et al. [216] and oxyfuel combustion Faria et al. [217] together with post-combustion [218] approaches have significant potential for CCUS in the cement sector. As a result, the range of yearly CO_2 storage capacities for various technologies is 25,000 tonnes to 2 million tonnes. For example, the Colorado, USA-based Holcim Portland Cement Plant plans to run a trial system that can capture two million tonnes of CO_2 annually [215]. According to Cavalett et al. [219] converting cement factories to oxyfuel combustion technology can reduce the related impact of climate change by 74%–91%. It was shown that using oxyfuel in conjunction with biomass fuels can result in negative CO_2 emissions of between 24 and 169 gCO_2, or equivalent, for every kilogram of clinker produced [219]. More research is required to determine the GHG emissions and possible carbon savings for various CCUS systems, given the variety of technologies appropriate for the cement sector. Izumi et al. [220] for example, suggested GHG emission calculations for mineral CCUS technology that might be applied to the creation of LCA inventories. While studies have demonstrated the promising potential of CCUS for the decarbonization of the cement industry, more comprehensive life cycle assessment (LCA) research focusing on various technical systems is required to project carbon emission reductions more accurately.

2.3.6.5 Supplementary cementitious materials (SCMs)

Using new low or zero-carbon concrete technologies to reduce the carbon footprint of concrete manufacturing is an appealing strategy for lowering the carbon emissions of the construction industry. These innovations mostly center on improvements in the binder system, where a less carbon-intensive material replaces cement either totally or in part. However, waste valorization methods could also be used to lower the carbon emissions associated with the manufacture of aggregates. SCMs are extensively utilized in the concrete industry, either as a partial substitute for clinker in the manufacturing of blended cement or as a substitute for cement in the manufacturing of concrete. SCMs can be extracted from a variety of materials, such as industrial wastes, calcined and raw natural minerals, and ash from trees and farms. Using SCMs typically leads to a significant decrease in carbon emissions because they don't require clinkering procedures. Moreover, through waste valorization, the use of SCMs made from industrial byproducts encourages CE [221]. The primary obstacle to adopting SCMs is the limited availability of traditional SCMs including FA, GGBFS, and silica fume (SF). As a result, it is important to identify growing sources of new SCMs. The research on novel SCM resources and their long-term impact on the durability and performance of concrete was evaluated by [222]. Moreover, numerous research have covered the technical elements of employing SCMs in concrete technology

[223]. Nevertheless, a thorough analysis of the contributions made by different SCM types to carbon reduction methods has not yet been conducted. The possible carbon savings of SCMs derived from various resources are covered in this section.

The most widely utilized SCMs in the manufacturing of concrete come from industrial waste. The most widely used additives in the manufacturing of cement and concrete globally are SF, GGBFS, and FA. Numerous studies have examined the consequences of employing these SCMs in the manufacturing of cement and concrete [224,223]. SCMs are advantageous in lessening environmental consequences in addition to enhancing the engineering qualities of concrete [225]. Tushar et al. [226] for example, found that substituting 50% of the world's cement output with FA and GGBFS can save 209 billion dollars in costs and reduce CO_2 emissions by a total of 2745 million tons. According to Hossain et al. [227] employing different kinds of traditional SCMs can reduce greenhouse gas emissions by 10 - 28% and the global warming potential (GWP) by 20 - 38%. Similar investigations also showed comparable results [228]. It's been debatable in recent years how conventional SCMs fit into the long- and medium-term net-zero carbon goals. This is mostly because of several limitations, including the scarcity of well-liked SCMs made from industrial byproducts and the related problems with supply chain management and transportation. Strategic use of SCMs is especially important since, according to Miller [229] the distance and method of transportation of SCMs may outweigh their contribution to GHG emissions. The relevance of SCMs' market limitations in LCA studies was highlighted by Arrigoni et al. [230] who concluded that in most cases, SCMs with an unrestricted market can cut GHG emissions. It's interesting to note that GHG emissions from restricted SCM replacements may be even higher than those from regular OPC concrete if they are utilized inefficiently, such as when transported over large distances. They also found, in line with Miller's [229] findings, that raising SCMs does not always result in a reduction in concrete's greenhouse gas emissions.

2.3.6.6 Alkali-activated materials (AAMs)

Alkali-activated materials (AAMs), including geopolymers, are acknowledged as environmentally beneficial building materials that significantly lower carbon emissions. AAMs have a good potential to serve as an alternative concrete technology in areas with locally available raw materials, even though they might not completely replace OPC concrete globally. Depending on the presence of an aqueous solution of alkali hydroxide, silicate, carbonate, or sulfate activator, AAMs are commonly classified into two groups: one-part (also known as "just add water") and two-part (also known as traditional) AAMs. In one-part mixes, the binder matrix is prepared by adding simply a dry combination containing a solid aluminosilicate precursor and a solid alkali-activator to water [231]. As the precursor in AAMs, a variety of aluminosilicate binders, such as FA, GGBFS, metakaolin, and calcined clay, can be used. This section focuses on the potential of AAMs in reducing carbon emissions, even if several studies in the literature [232-235] evaluated the technical elements of developing AAMs. Unlike the other alternative technologies examined in this research, the possibility of reducing AAM carbon emissions has been extensively studied through life cycle assessments (LCAs) in the public domain [236]. Compared to OPC concrete, AAMs can reduce CO_2 emissions by more than 50%, making them a viable choice for short-term decarbonization plans.

However, the results of this research highlight the crucial role that activators play in deciding how much carbon AAMs can save. Most carbon emissions in AAMs, according to Robayo-Salazar et al. [237] and Fernando et al. [238], are caused by alkali activators such as sodium silicate and sodium hydroxide. Consequently, it is important to thoroughly examine the usage of chemical admixtures when producing low-carbon AAMs, particularly when the goal strength is high. An additional crucial element in creating AAMs with a markedly diminished carbon footprint is the accessibility of indigenous raw resources for utilization as precursors. The carbon footprint of AAMs may rise due to the transportation of raw materials and the use of low-reactivity precursors. Using appropriate industrial wastes as activators in one-part AAMs is a possible substitute for carbon-intensive activators. Desulfurization dust was employed by Adesanya et al. [239] in place of commercial sodium hydroxide activators. They provided proof that employing these kinds of industrial byproducts can lead to the production of cleaner AAMs with a smaller carbon footprint. Comparable results were also seen when one-part AAMs were activated with RGP, RHA, and lime kiln dust 240-242]. The environmental effects of newly developed AAMs that use other kinds of waste in place of chemical activators need to be further investigated.

2.3.6.7 Recycled concrete

In sustainable concrete construction, recycling leftover concrete is a standard procedure. Concrete has seen some preliminary use of this technology in place of natural aggregates. However, the viability of utilizing leftover cement paste to create recycled cement has been investigated in several recent research. With the amount of construction waste produced constantly rising and the pressing need to move the construction sector toward sustainability, recycling of construction and demolition wastes (also known as CDW) has been a key field of research in the last several decades. Many articles have documented the use of recycled aggregates (RA) in place of natural aggregates (NA) in the creation of recycled aggregate concrete (RAC). A review has been conducted of the progress made in comprehending the mechanical and durability features of RAC [243-245]. Additionally, basic studies have been carried out to evaluate how much RAC technology contributes to reducing the environmental impact of the concrete sector [228,246]. It has been proven that using RAC technology can lower the carbon footprint associated with producing concrete. On the other hand, one should carefully evaluate the significant significance that determining factors play. The transportation distance to concrete manufacturing plants and landfills for the disposal of construction and demolition waste is one of the important factors [247-249]. In this sense, eliminating the lengthy transit of CWD or NA may result in considerable reductions in carbon emissions, even though the carbon savings from utilizing RA instead of NA may be minimal. Moreover, carbonated RAC (CRAC) technology offers a remarkable way to harness the potential for reducing carbon emissions. CRAC is commonly used to enhance RA quality through carbon mineralization, while it can also be advantageous for carbon sequestration plans. Tan et al. [250] found that RA carbon-conditioning is a useful technique that offers a workable application of CRAC. Because carbonated RA may absorb carbon, Xiao et al. [251] observed that concrete prepared using carbonated RA has 7.1% - 13.3% reduced carbon emissions compared to concrete manufactured with NA or non-carbonated RA, respectively. Combining RAC and CRAC with another waste valorization technique, like using by-products as SCMs or precursors for AAMs, is an intriguing way to increase carbon savings [252,253]. Moreover, numerous research papers in the literature indicate how recycled concrete have been shown to help the concrete sector decarbonize. Considering innovative applications, such as reusing recycled concrete as filler in tetrapods, offers an additional avenue for sustainable waste utilization. This should be considered when developing strategic carbon neutrality paths.

2.3.6.8 Carbon sequestration in concrete

One viable method for decarbonizing concrete is to incorporate carbon sequestration into the curing process. The ability to bind CO_2 into thermodynamically stable calcium carbonate ($CaCO_3$) is provided by materials that contain calcium [254]. Precast concrete's carbon curing process was one of the technology's early uses. For example, Shao et al. [254]. showed that when precast concrete was exposed to 100% pure CO_2, the binder mass took up between 9% and 16% of the carbon. The creation of novel CCUS technology for the concrete sector has been the focus of numerous initiatives. Carbonation of recycled aggregate concrete (CRAC) carbon sequestration in magnesium oxide binders, CO_2 mineralization in synthetic cementitious materials (SCMs) and industrial by-product fillers, and CO_2 dissolution in concrete mixing water are some of the new methods [255]. Even while our understanding of the various CCUS methods used in the manufacturing of concrete has advanced significantly, their environmental impact is still up for debate. Numerous studies highlighted how promising current CCUS technology is at sequestering carbon. Dixit et al. [256] for example, looked at the carbon uptake of freshly made UHPC mixtures made from GGBFS. It was discovered that, while the compressive strength was not greatly impacted, a carbon absorption of 80 kg CO_2 per m^3 of UHPC could be attained by replacing 30 weight percent of the cement with GGBFS. Shao et al. [257] assessed the environmental advantages of basic oxygen furnace slag (BOFS) and carbonated yellow phosphorus slag (YPS) using a life cycle assessment (LCA). They found that although aqueous carbonation reduces carbon emissions, it poses major issues with water use. However, certain research has pointed out significant constraints related to carbon sequestration in concrete. Zhang et al. [212] conducted a review of the body of knowledge regarding cement-based composites' carbonation curing. They concluded that while carbon-activated binders with low CO_2 emissions are a viable solution, a significant drawback is that full carbonation isn't achieved throughout the depth of concrete. According to Ravikumar et al. [258] the net CO_2 benefit of Carbon Capture and Utilization (CCU) concrete was negative in experimental datasets that were examined. Additionally, they stressed that improving the net CO_2 savings via CCU in concrete requires reducing the amount of electricity used for carbon curing and raising the compressive strength through CO_2 curing [258]. Consequently, to carefully assess the carbon-saving potential of various CCUS technologies in the concrete industry, thorough experimental and life cycle assessment (LCA) investigations are needed.

With a potential capacity to sequester up to 2.6 tonnes of CO_2 per tonne, biochar is a carbon-based substance that is primarily created by the pyrolysis of biomass wastes [259]. According to certain research, adding biochar to cement at low concentrations (around 5 weight percent) may improve the cement hydration process and boost compressive strength [260]. According to Dixit et al. [261], an increase in hydration degree may result in less cement being used in concretes with low water-to-cement ratios, such UHPC, and a consequent decrease in carbon emissions. Numerous studies have been conducted in the literature to examine the impact of biochar on the engineering qualities of concrete [262]. However, some research has investigated the viability of employing biochar as a carbon-sequestering addition in the production of concrete [263]. Therefore, by recycling waste, this method may help to promote CE and lessen the carbon footprint associated with the production of concrete [263]. The pyrolysis settings and activation techniques, among other manufacturing parameters, are the primary determinants of the carbon-capturing capacity of biochar in concrete. However, studies have shown that pyrolysis in concrete can cut greenhouse gas emissions by 25% [264]. Furthermore, biochar incorporation may be used to create concrete that is both carbonnegative and carbon-neutral, according to recent LCA research. For example, Chen et al. [265] reported that concrete that contains 30% weight percent biochar in addition to other SCMs may be carbon negative. They proved that 30 weight percent biochar aggregate and 9 weight percent metakaolin could sequester 59 kg of CO_2 for every tonne of concrete. Furthermore, combining biochar with calcium carbonate cement may make it easier to produce concrete that is carbon neutral; nevertheless, more coordinated research is needed to examine the technical characteristics of these composites [266]. Overall, the increasing amount of study on the use of biochar in concrete technology points to the technology's promising potential to lower concrete's carbon footprint. However, to fully comprehend its carbon-saving effectiveness, extensive LCA studies are needed.

2.3.6.9 Biomineralized cement and living building materials (LBMs)

Microbial biomineralization is the basis for the development of bio-cement technology, which aims to improve the sustainability of newly produced building materials. The utilization of calcium carbonate biomineralization processes in construction materials was reviewed by Beatty et al. [267]. Among biomineralization methods, engineered living building materials (LBM) provide a novel technology that adds various functionalities to building materials using biology [268]. Sand-gelatin structural scaffolds are biomineralized by photosynthetic bacteria that can produce microbially induced calcium carbonate precipitation (MICP), such as Synechococcus sp [269] and Escherichia coli to create LBMs [270]. As a result, LBMs can acquire strength without the use of cement. Because CO_2 sequestration during cell growth has such a promising potential, this method has garnered a lot of attention. During photosynthesis, sequestered CO_2 is liberated and reacts with water to produce biomineral calcium carbonate. According to Heveran et al. [269], LBM is a technology that gives building materials multifunctionality sensing, responsiveness, and regeneration through biology. However, since LBM is still in its infancy, more study is needed to determine its scalability and other possible uses, like carbon sequestration [271]. Additional uses for biomineralization include better self-healing cement-based composites and bacterial treatment of waste-based cementitious materials. According to Sharma et al. [272] adding up to 40% sandstone powder to mortars together with bacterial treatment can enhance mechanical and durability qualities while reducing carbon emissions. The ability of LBMs to self-heal was investigated by Delesky et al. [273] using biomineralizing Synechococcus sp. PCC 7002. They found that following seven days of physical re-crosslinking of the hydrogel scaffold, injured LBMs recovered 100% of their compressive strength. Study analysis indicates that biomineralization presents a promising way to lower cement consumption in the building sector by fostering calcium biological carbonate precipitation for cement-based composite self-healing, repair, and rehabilitation, or by creating cement-free LBMs. Since biomineralization is still a relatively new technology, more investigation is necessary to fully understand its implications for the net-zero carbon concrete market in the coming years.

2.4 Literature Review Summary

The four steps involved in producing Portland cement are described in Chapter 2: (1) raw material extraction, crushing, and grinding; (2) material preparation and mixing; (3) kiln burning of the prepared mix; and (4) grinding of the burned product, or "clinker," along with approximately 5% of gypsum. The chapter also includes a review of the literature on the issues related to cement manufacturing that were discussed in Chapter 1. The overuse of raw materials, the impact of overburden trash dumps from quarry mining, and CO_2 emissions are the main causes of the issues. Cement production is one of the main sources of air pollution because, in addition to being one of the energy-intensive industries, it also requires the processing of raw materials that usually contain sulfur and nitrogen and is primarily dependent on fossil fuels. One important option for the cement production business is the digitization adaption. Temperature, level, vibration, displacement, and nanomodified smart cement-based sensors are the five primary types of sensors utilized in the production of cement. Throughout the production process, temperature sensors are utilized to monitor the material's temperature. Systems engineering principles can be brought directly to bear throughout the production cycle: digitalization makes it possible to gather performance data that can be utilized to build optimization models that can assist in addressing some of the related issues facing the cement manufacturing sector.

The chapter also examines the remedies that have already been offered in the literature for the issues raised here, as well as how our research will complement the numerous effective solutions already in place.

Chapter 3 – Research Method

The framework for analysis used in this research endeavor is covered in this chapter. The goal of this study is to find approaches that can be modified to:

- Minimize overburden waste dumps and optimize raw resources for the quarry. As a result, a mix of quantitative mathematical modeling, mining software, and an examination of the procedures related to life cycle management in the cement production industry were employed in the study.
- Multiple regression, non-linear regression, and linear regression research methodologies were employed for CO_2 emission prediction to investigate potential causal or non-causal models of the correlations among the proposed variables. The methodology is designed to recommend ways in which operational variables can be used to predict CO_2 which will have overall performance. This was completed by using statistical modeling at the aggregated cement calcination level.

The goal of the research is to better understand and develop ways to improve the effects of social and environmental impact on society as mentioned in the first and second chapters of this dissertation.

3.1 Raw Material Optimization and Overburden Wasting Dump Control

Cement producers work hard to keep the cost of cement production down. Effective quarry management is also recognized as a crucial step in the production of cement, with significant potential for cost savings and other environmental benefits. For the Union Bridge limestone quarry, the study optimized the quarry, identifying different geological formation components as significant influencing factors. After that, each activity is examined separately and its potential for improvement is assessed by contrasting it with other relevant activities related to the location and geology of the area. The influence of every activity's improvement potential is then measured in terms of raw material optimization.

3.1.1 Quarry Planning and Production Sequencing

The concept of using 3D modeling in cement quarry planning and production sequencing is not as common as compared to large mining operations like gold or copper. In Chapter 2 some literature reviews detailed some of the techniques used for the optimization of the limestone quarries. To achieve an optimized raw material requires that multiple levels of limestone $CaCO_3$ percentage with levels of impurities must be blended. To do this with complex geological formations is not simple. Therefore, the mathematical complexity of reaching the optimal chemical composition requires that advanced computer software be used. Unfortunately, most of the developed 3D modeling software packages are made for mining operations, not cement manufacturing quarries. Given this, research conducted for such cement complex limestone raw material models is mostly done using mathematical integer models which do not look at all aspects of mining. On the other hand, common commercial software packages such as Leapfrog/Edge, Datamine, Vulcan, Surpac, MineSight, and Micromine are adapted by metal mining. As already addressed by designing efficient quarry operations, vast quarrying areas can be reduced, excessive overburden removal waste can be avoided, and mining raw material quality can be improved. This is made possible using 3D modeling tools. The 3D software packages need to be adjusted to meet the goals of cement manufacture because they were created for mining businesses rather than cement quarries. This is because they are needed for quarry planning and production sequencing. The 3D modeling of the cement quarry uses the raw mill and kiln-dependent quality targets mentioned in this manuscript's Section 3 as a cut-off. The Union Bridge quarry employed GEOVIA, an internally modified 3D modeling technology, for the case study. With certain adjustments, the GEOVIA Surpac and Whittle Software tool was applied to match the planning and sequencing requirements to produce cement [274]. The purpose of this section of this chapter herein is not to provide specific detailed steps about the sequencing of production and mining planning for limestone but to give an overview of how the GEOVIA Surpac software was used to develop the block modeling, mining sequencing, and its impacts. It is meant to provide an overview of how existing (asset inertia) mining software can be used in cement quarry planning. Note that the constraints for the mining modeling and quarry optimization is based on Table 2. The other intent of this section of the chapter is to provide process controls added during the research study to help reduce waste which will have a less negative impact on the environment.

3.1.1.1 Block modeling for cement quarry

Block models, which consist of computer-generated "bricks" representing small pieces of rock in a deposit (ore, limestone) and rubbish (overburden), simplify an image of an ore body and its surroundings. Estimates of element grade, density, and other properties of geological or engineering entities are stored in each "brick," or cell. Carefully defining the chemistry of the natural deposit (limestone and overburden) and determining the cut-off chemical target, which is necessary for cement manufacturing, are the two most important data points in cement quarries. When modeling the blocks, a variety of approaches, such as the Inverse Distance Squared, Ordinary Kriging, Multiple

Indicator Kriging, and other estimation methods, are used to assign each block a chemical percentage (CaO, A_2O_3, K_2O, SiO_2, etc.) and densities. Drill cutting lab analysis and exploration drilling are used to collect the chemistry data. A typical standard block model architecture for Surpac-based cement quarry modeling is depicted in Figure 20.

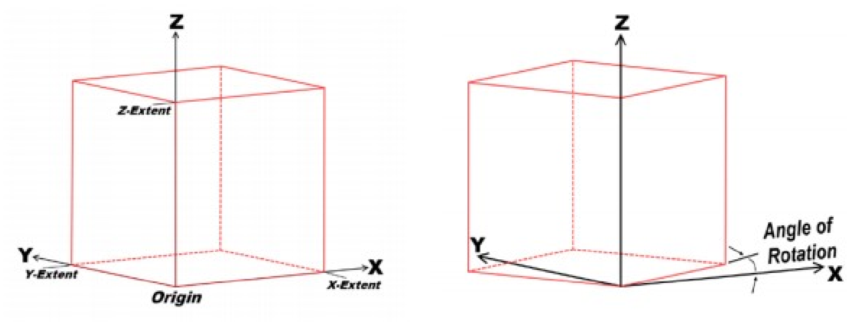


Figure 20 shows the Standard block model framework [274]

This construction is made up of separate blocks, each having an X-, Y-, and H-increment (length, width, and height) (Z-increment). The block position (Xmin, Ymin, Zmin) can be specified using a block origin or a centroid (Xc, Yc, Zc). It is usual practice to indicate the number of blocks in each coordinate axis direction to define the whole feasible model structure. It is important to remember that not all modeling approaches require a completely "filled" block model; some modeling techniques allow for the absence of blocks entirely. A common model view in Surpac is displayed in Figure 21.

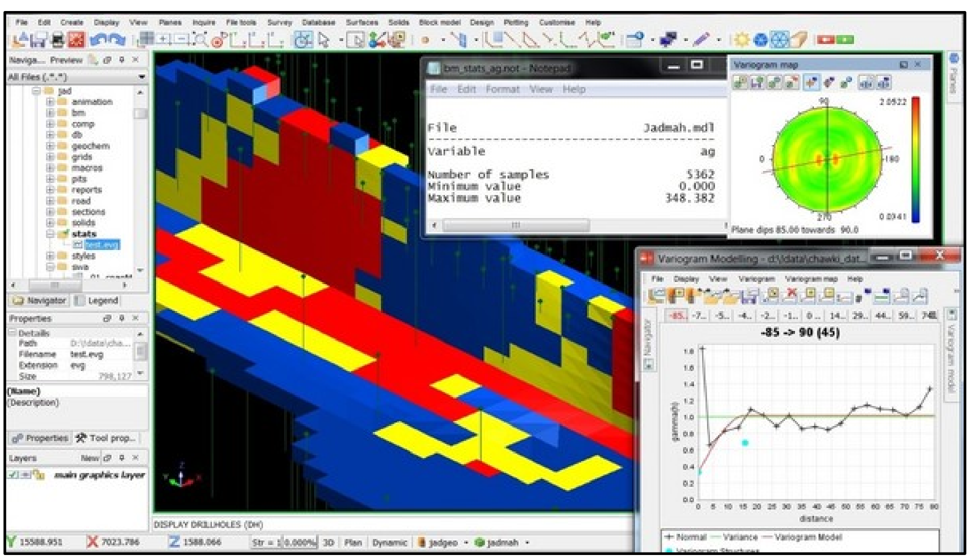


Figure 21 shows a typical view of the Surpac 3D modeling tool [274]

The block model is essential to the design of an optimized quarry that can be mined to fulfill the design's intent and accomplish the objective of the cement producing facility. The secret is that the goal of the cement quarry block model can be accomplished by modifying the mining 3D model tools. The computation block model is utilized to determine the quarry's reserves or the amount of usable volumetric limestone that is present on site. In the mining industry, tonnage (the measure of the amount) and grade of an ore deposit well, with the derived anticipated economic valu,e are determined through the calculation of ore resources and reserves. It can be carried out to evaluate mineral resources from the outset as well as to determine the number of ore reserves that remain after mining. It can be carried out to evaluate mineral resources from the outset as well as to determine the number of ore reserves that remain after mining. Since the quantities of minerals and structural elements in different parts of a deposit might vary, a geological model of the mine enables us to modify our mining strategy and select the best exploration and mining technique. There are two main components to an area's total mineral endowment: identified resources and undiscovered resources. These are further separated according to how well-informed people are about the deposits and the state of the economy. The following definitions of reserve and resource words are taken from the U.S. Bureau of Mines and U.S. Geological Survey Circular 831[275] and are either paraphrased or cited from it. The following describes the several definitions that were thought to be used to locate resources or unknown resources.

- *Resource* - an area of the Earth's crust where naturally occurring solid, liquid, or gaseous materials are concentrated to the point where it is thought to be economically possible to extract the commodity, either now or in the future.
- *Identified resource* - a resource whose precise geologic evidence allows for the estimation of its location, grade, quality, and quantity. Economic, marginally economic, and subeconomic resources have all been identified.
- *Undiscovered resources* - unknown masses of mineral-rich material, the presence of which is inferred from general (regional) theory and information.
- *Reserve* - that fraction of an identified resource from which a viable mineral or energy commodity can be economically and lawfully exploited now of determination. For lack of a better term, the term "ore" is occasionally used to refer to deposits of nonmetallic minerals as well as certain metallic mineral commodities.

The terms "measured," "indicated," and "inferred" resources can be used to refer to identified subeconomic resources as well as identified economic resources (reserves).

- *Measured* - materials whose quality and quantity have been established by quantitative data, including suitable analyses, from closely spaced and geologically well-known sample sites, with a margin of error of less than 20 percent.
- *Indicated* - materials, the quality and quantity of which have been determined using a combination of reliable geologic inferences and measurements as well as studies and measurements.
- *Demonstrated* - a phrase used to refer to the total amount of materials in both indicated and measured resources.
- *Inferred* - components in known but unknown deposits, the quantity and quality of which have been approximated using geologic projections.

The terms "hypothetical resource" and "speculative resource" apply to undiscovered resources and are useful when estimating resource endowment.

- *Hypothetical resources* - unknown materials that, given known geologic circumstances and recognized mining districts, may logically be predicted to exist.
- *Speculative resources* - Undiscovered materials may exist in as-yet-unknown deposit types that need to be recognized or in known deposit types in geologic contexts where no prior discoveries have been made.

Industry frequently uses the terms "proved," "probable," and "possible" to describe economic assessments of ore in particular deposits or locations. "Proved" is quite like "measured." The terms "possible" and "probable" often refer to estimations of partially sampled deposits; both are included in the definition of "indicated" as it is used here. Almost generally, the estimate of reserves and resources provided by the survey author for a district or area should be presented in a way that obscures the specific statistics for properties. It is acceptable to quote published estimates if they are correctly attributed. The following mathematical techniques are applied in the models to determine the reserves or resources:

The *polygon method* is a well-known and traditional method based on a straightforward geometric algorithm. We build a polygon around each hole to identify its area of influence, and we then assign the same values to the total volume directly beneath the polygon as we did to the drill hole from which the polygon was constructed. We'll examine this approach in more detail soon.

Another method, known as the *triangle method*, demands that we form triangles by joining adjacent holes. Each triangle's included area is given the characteristics of the weighted average of the three holes that make up the triangle, rather than the characteristics of a single hole. The length of the drill holes is the basis for the weighing of the three holes.

The *inverse distance method* is a more intricate plan where a hole's contribution is weighted based on how far it is from the block where the estimate is to be made. A hole's value is weighted more heavily based on its proximity to other holes in the area.

Geostatistical methods employ three-dimensional spatial statistics are used in mineral reserve estimation to enhance the estimate's accuracy. A specific distribution model, such as one in which the samples are independent of one another and the data are normally distributed, must be used when performing classical statistics. The orebody typically has too few samples for us to assign a distribution to, and the samples themselves are frequently correlated, meaning they don't meet the independence criterion of traditional statistics. Given that the drill holes, or samples, are scarce due to their high acquisition costs, frequent bias, and almost constant smaller quantity than required, geostatistics is an effective tool for enhancing the estimation's quality.

A solid prediction of the grade's spatial distribution, or another relevant attribute, is a necessary condition for making a credible estimate of the orebody's grade. The sample data and a model called a *variogram*, which is used to depict the correlation between the samples, are used to complete this geographical estimation. The method known as kriging is frequently used to achieve this estimation. *Kriging* offers the variogram the best possible interpolation; the method is comparable to straightforward interpolation, such as that found in the inverse distance algorithm, but it differs in that it allows us to account for geological and associated property knowledge. We can determine that all of the points that make up a given feature should have similar or identical properties based on our understanding of geology. This is an instance where samples are correlated. We can utilize this information to enhance the grade estimate, or whatever, at locations where we haven't sampled using geostatistical techniques. Geostatistics is a science that continues developing and getting more precise.

3.1.1.2 Quarry Ultimate Pit Design planning for cement quarry

A surface mining method called open-pit mining, or opencast mining, involves taking minerals out of an exposed pit in the earth. The most popular technique for extracting minerals worldwide is open-pit mining, which doesn't use tunnels or extractive techniques. The process of optimizing the exploitation of mineral reserves for maximum added value while staying in line with the strategic aims and objectives of the business firm is known as quarry design planning. Most mining professionals are familiar with the strategy, which has significant operational benefits. To do this, the 3D computer modeling technologies discussed here are employed. The previously stated reserve computation determines the boundaries of the mineable minerals, not the deposit's geological periphery, and is input into a 3D software application for a possible open-pit quarry or pit design. These elements are typically considered as pit design criteria by material type and/or geotechnical domain before beginning a pit design:

- Berm width
- Safety Berm width and placement intervals (if requested or required)
- Batter angle (bench face angle)
- Bench Height
- Inter-ramp angle (IRA) limits
- Overall slope angle (OSA) limits
- Ramp width
- Ramp gradient
- Switchback width and gradient
- Minimum Radius for Curves
- Truck Stopping Distances (Loaded & Unloaded – at maximum allowable or achievable speeds)
- Drainage planning needs, including drainage gradients for benches and berms
- Minimum mining width – pit bottom, bench ends, stage cut-back widths
- Preferred effective bench mining width.
- Safety Features required (e.g., safety ramp run-offs; etc.)
- Geotechnical zones to avoid ramp placement.

The initial phase of quarry planning, known as the Strategic Mine Plan, establishes the project's technical and financial orientation. The project's success on the social, economic, and environmental fronts depends on choosing the right approach. The ultimate pit requires input data. Technical optimization with pit optimizations from GEOVIA Surpac requires essential inputs for the model. These fall into the following categories:

Geotechnical data - In Surpac, the maximum angles are restricted to the azimuths of the cardinal points (N-S-E-W-NE-NW-SE-SW). Geometric zone definitions can be avoided since the slopes are based on the type of rock. This enables different slopes to be obtained depending on the depths as well as several maximum slopes to be set to these blocks based on their "rock type" feature. Parameters considered for slope design while taking geotechnical concerns into account are shown in Figure 22.

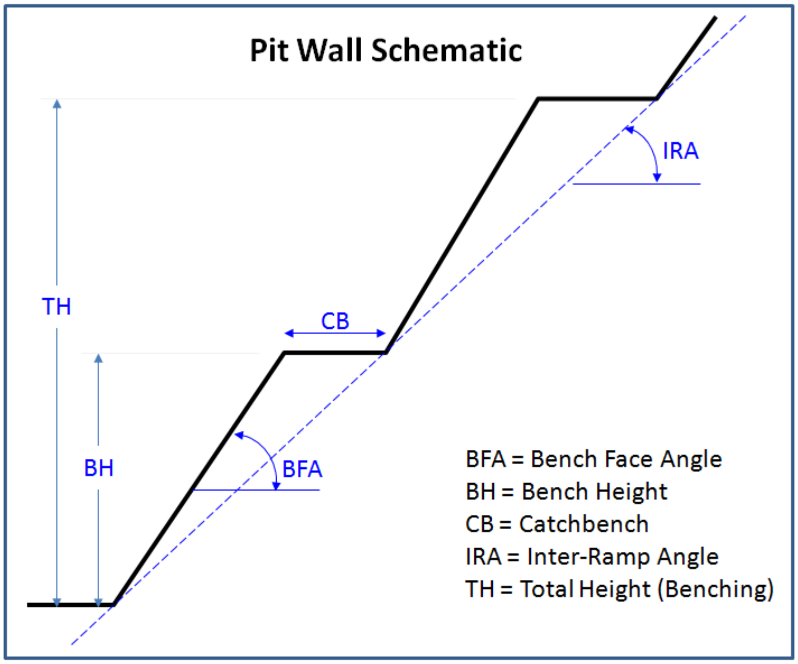


Figure 22 shows a typical view of the pit wall schematic

Pit/quarry wall failures are a possibility; hence, the geotechnical part of the design is very important. There is all the data needed for the modeling and design. The economics of mining are materially improved when slope angles on an open pit mining operation become steeper. Slope failure risk may also rise as slope angles steepen. Because they can be disastrous and involve several fatalities, equipment damage, and the temporary or permanent closure of a mine, slope failures are by nature expensive occurrences.

Economic data – The economic data are the most sensitive elements for determining the final pit form and the ore quality cut-off grades. There are several factors to consider when assessing the price at which metal is sold and the cost of processing extraction. The market price per ton of copper, which is now $7,000, is the default starting amount. This is the cost that will be subject to several reductions to examine how the different pits behave. The economic data includes the extraction cost ($/t). The cost of extracting each type of sterile rock or ore varies. Based on the selling price, the pit optimizer will assess each block to determine if it is sterile or ore. The optimization simulation considers the cost of processing the ore. The block's content alone allows it to be eliminated from the optimizer if it doesn't contain enough metal to be classified as ore. Surpac pit optimization will handle them as sterile by default and won't even attempt to determine their value. If the content of the block (as determined by the software's algorithms) makes processing profitable, the block will be processed. This could be a serious drawback. The model assigns a price of $/ton to metal. It remains unchanged over time. Pit optimization manages and optimizes pits that contain multiple metals and sets distinct pricing for various ore kinds (if they are in different blocks).

Mining Data – Data employed for mine planning encompasses various factors such as ramp width, gradient, switchback width, minimum curve radius, truck stopping distances (both loaded and unloaded, at maximum feasible speeds), and additional parameters. Planning considerations extend to drainage requirements, encompassing gradients for berm and bench drainage, as well as specifications for pit bottoms, bench ends, stage cut-back widths, recommended effective bench mining widths, and essential safety features such as safety ramp run-offs, all of which contribute to determining minimum mining widths.

The primary objective of most of the pit designs discussed here is to produce technical-economic exploitation parameters, after which Net Present Value (NPV) is assessed and attained. From a technical perspective, optimization in the XZ and XY planes produces the best pits, which is provided by Surpac's pit optimization using the $/unit technique. The objective here is to increase revenue for the optimized pit. This isn't the case for cement quarries, where the need for a quality mix to fulfill the manufacture of consistently high-quality cement drives pit optimization rather than economics. Consequently, the mining operation cost, the chemistry targets, the geotechnical data, and the mining data are the essential input data for cement quarry optimization planning. As a result, the same optimization model for cement quarries cannot be utilized with the standard Surpac program for mining pits. As a result, some technical abilities are needed to modify the Surpac software so that it fits the cement modeling approach. For our study, this software manipulation was used. If this is the case, then a sufficient understanding of the cement manufacturing process and quality standards is necessary for the quarry planning design. A typical ultimate optimized quarry/pit design created with GEOVIA Surpac software is depicted in Figure 23.

Mining initiatives that are successful need both technical and managerial know-how. Well-informed counsel is derived from a wealth of information and vast real-world experience. A network of multidisciplinary experts facilitates communication between specialized disciplines, lowers risks, and creates reliable, workable mine plans. Having worked on all kinds of mining projects, from resource estimation to mine decommissioning, helps ensure that creative solutions that are affordable and safe for the environment will be derived. It is essential to have an unbiased, technically thorough opinion on the project's viability at every stage of mine development and operation. Effective due diligence reviews and audits help operations maximize profits by constantly optimizing production, assessing optimal quality, and decreasing risk, and increasing safety.

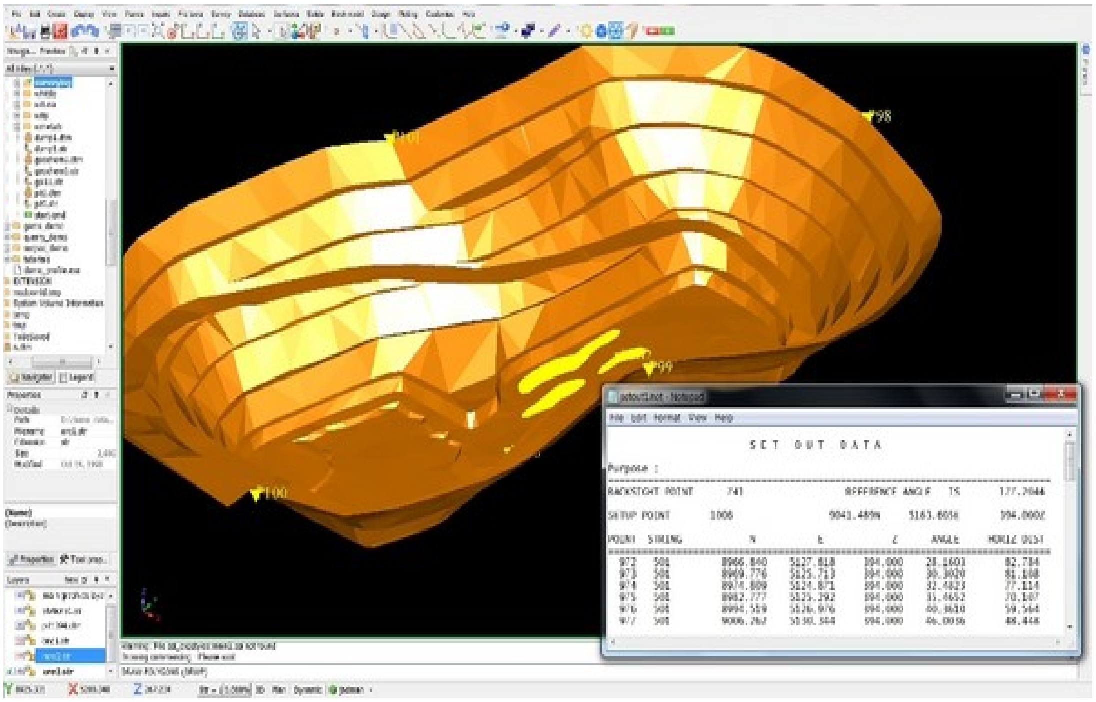


Figure 23 shows a typical Ultimate Optimization Quarry Design Using Surpac [270]

3.1.1.3 Quarry production sequencing for cement quarry

Achieving the right chemistry quality target for cement manufacturing and a lower cost of mining requires that mining sequencing of bench faces, and depth are achieved. Also, material movement during production is critical. As part of the quarry planning, the production scheduling optimization techniques must be achieved. This has not become common in cement quarry mining. This research study seeks to show how an optimization model with an efficient solution method can address the Long-term Cement Quarry production scheduling using GEOVIA Whittle Software. Figure 8 shows a typical generated long-range production schedule sequencing of material and quality to achieve an optimized quarry. This is critical to make sure that the quarry life is achieved based on the optimized quarry design and plan. Also critical is meeting the chemistry quality targets of the kiln by supplying 85% quality limestone to the raw mill with consistency and less variation. This helps reduce the wasteful use of raw materials and the overproduction of overburdened waste. The precise blending models in computer models and optimized sequencing allow for a reduced footprint of the quarry area, therefore reducing the destruction of the virgin vegetation and trees.

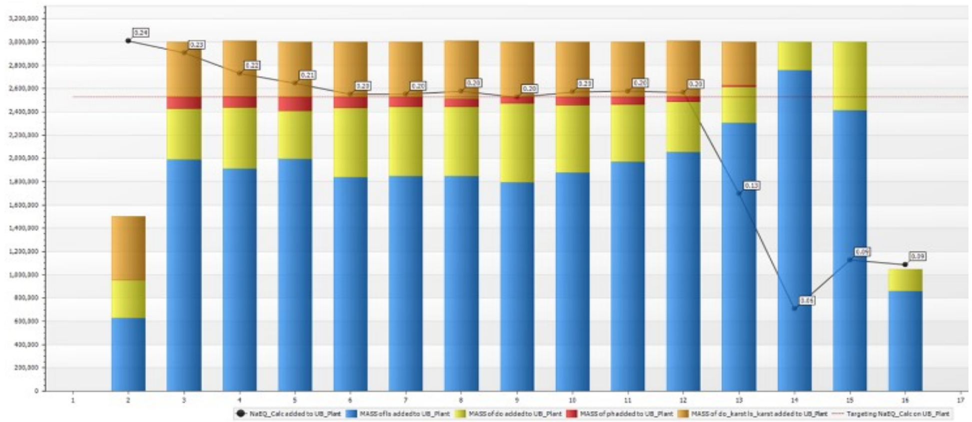


Figure 24 shows a typical production schedule for the different materials and chemistry

3.1.2 Quality control using data management systems and display to improve raw material optimization and reduce overburden waste dumps

Data-driven control loop tools are used to meet production mix scheduled chemistry targets and quarry design requirements in operation. In the cement manufacturing sector, this system architecture is distinct and the first of its kind. In the manufacturing sector, digital transformation, and the use of data to achieve operational excellence are quickly taking center stage. The idea is to make the most of current investments by utilizing data-driven analytics, technology, and underlying applications. It also depends on providing a seamless transition to digitalization and integrating data, assets, and resources with legacy systems. Furthermore, this contributes to the upkeep of plant sustainability at all stages and optimizes productivity and efficiency by leveraging data-driven analytics, technology, and underlying applications. Although the cement industry is adjusting to this new business model, it is still finding it difficult to completely accept the idea. Data extraction, data storage, data translation, visuals, and feedback loops are all part of digitization. It maximizes efficiency and minimizes human controls, which typically lead to numerous operational failures. Technical know-how and extensive infrastructure development are needed for this. It is uncommon to see graphical displays of cement quarry operations created using digitalization and data analytics. Most of the time, a single output data point based on a belt scale is provided for the quarry. The raw mill's quality has recently been adjusted using chemistry data from a cross-belt analyzer that was placed on the quarry beltline.

Regretfully, there is no feedback loop utilizing any of these data to enhance quarry design and raise quarry quality. As a result, there is a divergence from the ideal quarry operation and a high feed quality standard deviation from the quarry. Large garbage dumps and excessive mining of unplanned overburden have long-term effects on the environment and quarry life. The technical activities and data management interactions across multiple hubs are depicted in Figure 25 to provide feedback to the quarry's ongoing mining process as well as to calibrate and reconcile the numerous models that were used for the improvements. The architecture of the data management system aims to meet customer needs (cement manufacturing kiln feed quality), ensure that all engineering designs' intended criteria are met, and offer a closed loop for improving quarry operating processes.

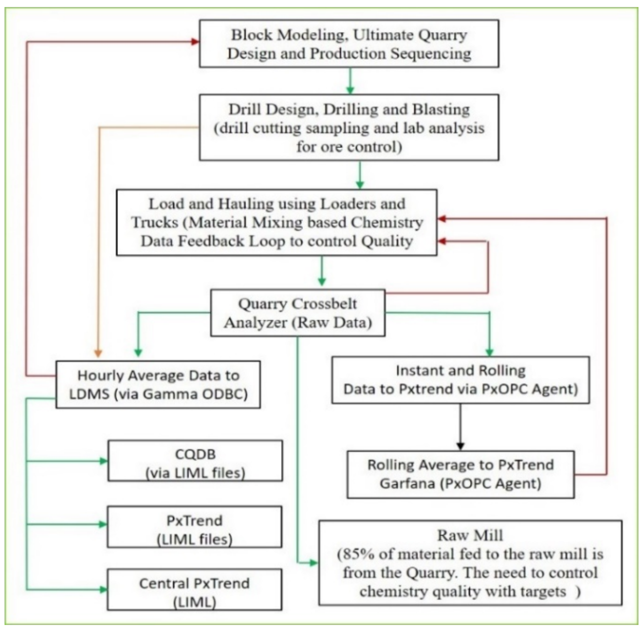


Figure 25 Technology Activities and interaction of Data Management Systems with the quarry system life-cycle process

A fundamental reimagining of how people, technology, and processes interact to produce and distribute value is known as "digital transformation." This project necessitated a significant infrastructure investment and involved setting up a tight feedback loop for database administration, as seen in Figure 25. Thermoscientific's cross-belt analyzer is used to acquire the raw chemistry analysis, and this is crucial. The raw chemistry data collected from the cross-belt analyzer is kept in two database systems named the LDMS (Laboratory Data Management System) and PXTrend. A thorough laboratory information management system is called LDMS. Because of its emphasis on cement production, PSCL's LDMS is distinct. Most labs have adopted electronic recording: LDMS expands the concept by combining equipment and analytical devices to reduce mistakes and boosting throughput. Test scheduling and tracking lead to increased productivity in the lab. To finish analytics, the data that has been altered and saved in LDMS can be extracted every hour. The chemistry information of drill hole cuttings can be entered into a database thanks to the LDMS. The GPS coordinates of the holes are included in the drill hole chemistry data. This set of data is used to calibrate the block model as feedback data and to improve the block model in quarry optimization. This permits customization of the quarry and satisfying KPIs (Key Performance Indicators). As the cross-belt analyzer can see, modern process plants generate massive amounts of data. Process values, reports, batch data, and status information from intelligent field devices are processed in automation systems, run through bus lines from milliseconds to milliseconds, and are output on multiple screens. PxTrend enables the retrieval of process data spanning many years from multiple automation systems and data sources across the entire organization. The architecture of PxTrend makes it easy for users to view process data on a PC, tablet, or smartphone (Figure 26). Operators can manage the mix blend in real time to fulfill targets by using tablets to view Grafana (PxOPC(agent)) graphically. Furthermore, PxTrend can save data in almost real-time and utilize all pertinent data to maximize process efficiency and boost plant production. Decisions based on safe data are aided by the data's long-term archiving and company-wide accessibility.

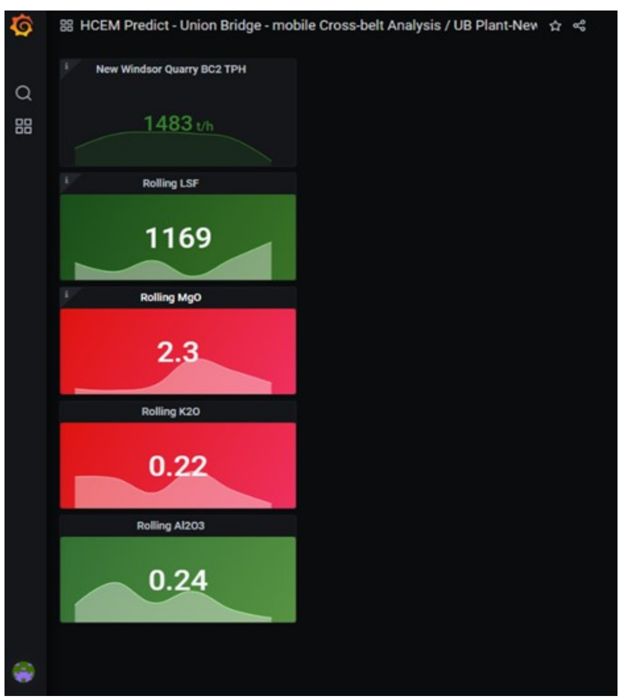


Figure 26 Data Dashboard Installed on Tablets in Loader Operator Cabin to help make instant changes to the material mix if off-targets. Red coded data means off target and green means on target.

Loader operators can make controlled additions of overburden (shale) and modifications to the limestone mix thanks to tablets fitted in their loaders that provide quality target data (Figure 26) in real time. Performance and management variations are understood through descriptive analysis using historical data from PxTrend. Additionally, statistical analysis is performed on the data to identify trends and compare them to goals. Better planning, control over the quality of the quarry's raw materials, and mining to fulfill the design's aim are made possible by this. For cement manufacturing efficiencies and the mitigation of environmental impacts, this part of optimizing operational processes through data management is essential. Data is used to better manage the production of dumps and overburden mining. The amount of raw materials like sand that are mined illegally in many developing nations is decreased by the perfect blend of high-quality raw material feed from the quarry to the raw mill, which is determined by data. The viability of the quarry operation and cement production depends on the implementation of a feedback control loop that ensures consistent quality material with minimal variation. Since some of the overburden mined can be used in the mix to achieve quality-controlled targets, the positive impact of such advanced data management tools to manage quarry operations also has a dramatic impact on the reduction of sand usage for cement manufacturing and a reduction in the production of waste dumps. This paper focuses on how current technologies can be modified to enhance operational excellence, and how data architecture management can be used to provide operational improvements that fulfill quality targets.

3.1.3 Quality Control using Data Management Systems to help with consistent raw material mix of Raw Meal

Data management systems used in the raw mill material mix control are built on data management platforms and comprise a range of components and processes that work together to help extract useful data and apply complicated analytics to produce an automated blend. Database management systems, data lakes and warehouses, analytics, data integration tools, and more can be among them. As previously mentioned, raw mill feed is a mixture of limestone from the quarry, whose quality is regulated to meet chemistry targets. Reclaimed ponded ash, which adds aluminum (obtained from power plants), sand, which adds silica, and reused iron slag, which adds iron, are added to this mix. The quality control architecture and data management system utilized to ensure that the raw mill feed quality matches predetermined chemical targets are depicted in Figure 27. There are separate silos and automatic feeders for every substance. Chemistry mix targets and computer-based analytics regulate the feeder's rate. By doing this, the blending silo's uniformity is improved before the material is fed straight into the kiln's inlet. Figure 27 depicts a closed control loop that is entirely automated and distinct.

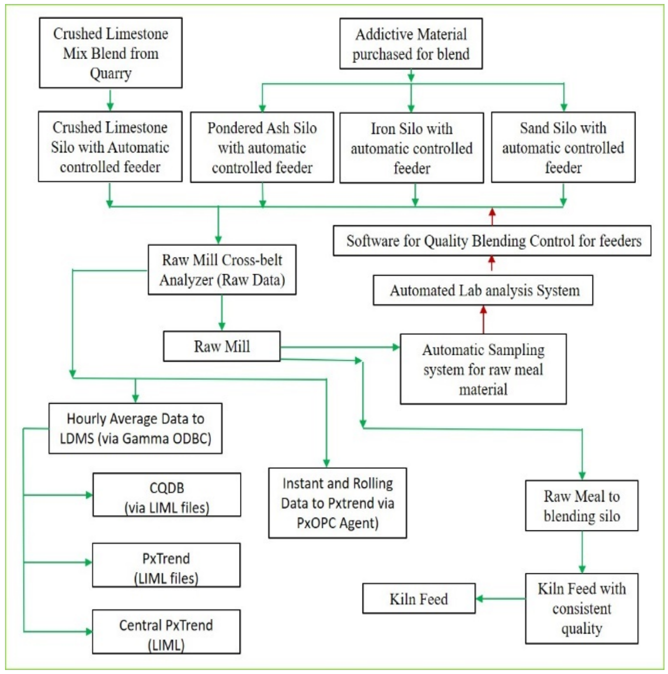


Figure 27 Data management architecture used to control the quality of raw mill feed

To determine the impact on quality, chemistry data gathered in 2019 and 2020 was compared before and after the quarry underwent step adjustments. As shown in Figure 27, these data are gathered in real time and kept in a database. The data of critical chemical targets used to assess the quality of material from the quarry, raw mill, and kiln feeds were compared using a process capability analysis.

3.1.4 Using Drill Blasting Date to calibrate Mining Models and Data Management Control loop

Drilling is the process of making holes in the earth to take core samples, drilling cuttings, and testing is the process of examining these samples to find out what minerals and other resources are present and in what quantities. A drilling design program was implemented by using innovative tools as drones and 3D topographic software. This requires selection of the area for drilling based on the mine models expanded on in this chapter. The concept is that by drilling and sampling and analyzing the samples in the lab, the data can be compared with the generated block model to see the reconciliation difference. In addition, the lab data can be also compared to the control loop data system to see if the data been generated matches what is in the field. This is a crosscheck method adopted to calibrate both the mining block models generated for the mining planning sequencing and the data management control loop system implemented. Figure 28 shows the workflow used for the calibration of the mine block model and data management control system.

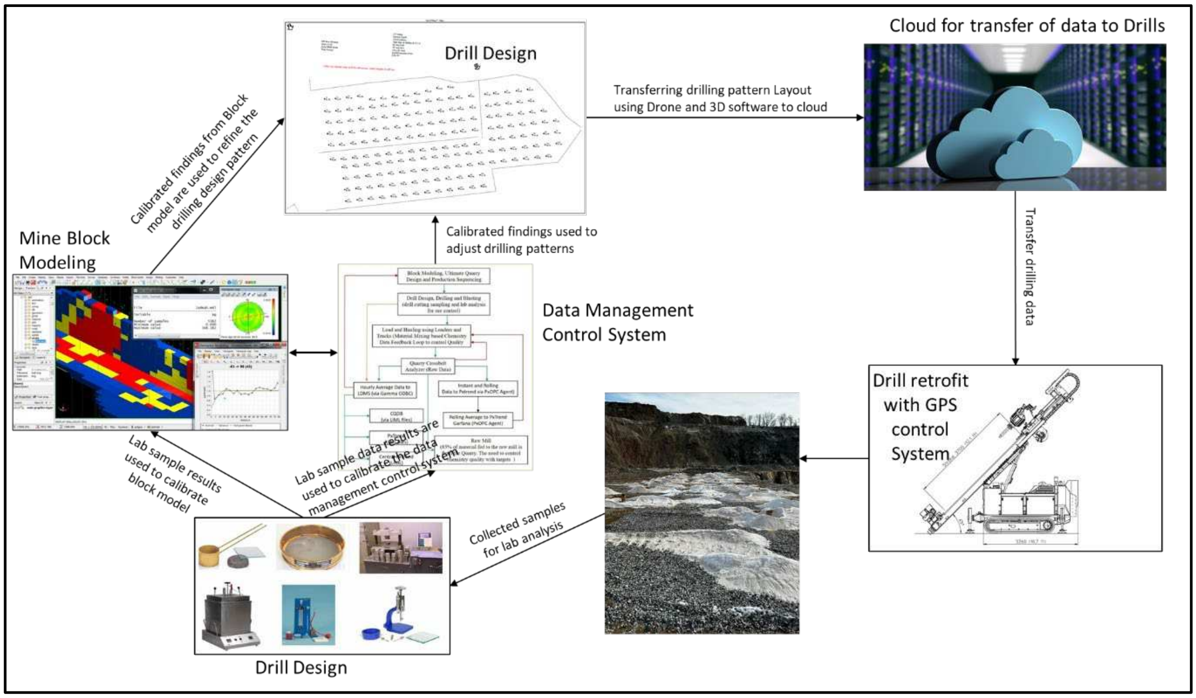
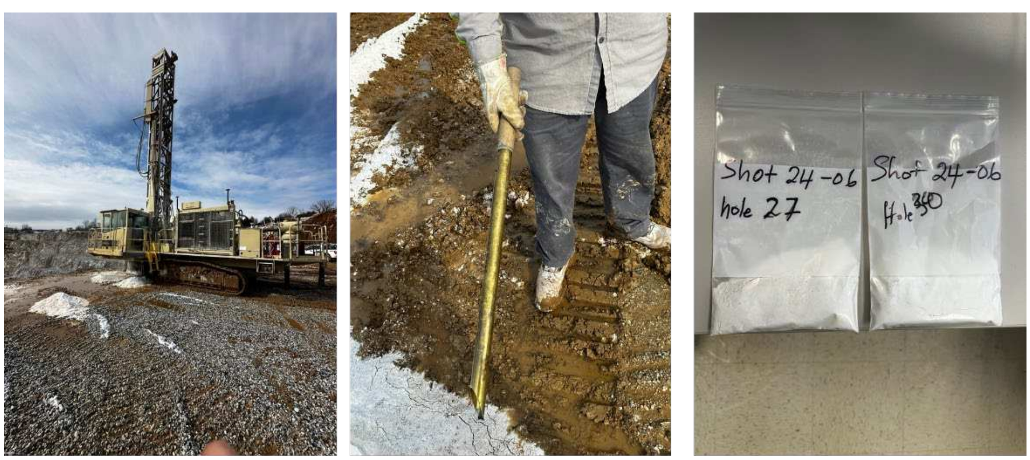


Figure 28 shows the workflow adopted to used drill sample lab data to calibrate the two systems adopted for this study

Figure 29 shows typical example of drilling patten designed and layout in the field using a drone system, drilling software and a 3D topo software. Drilling patten design are based on burden, spacing and height of the bench. The selection of distance for the spacing and burden is based on various nonlinear variables like geological, structures, required fragmentation, mine plan etc. Other factor in any explosion design is the size of the blast hole. The burden (distance from the blast hole to the closest free face) is determined by the blast hole diameter, the kind of explosive being used, and the kind of rock being blasted. Each additional explosion dimension is determined by the weight. For this research the key was to take advantage of the drilling cuttings and sample for chemistry analysis in the lab. Each design shot has each other hole sampled, and the sampling is staggered to make sure the area is well covered to capture all the geological formation.

Figure 29 shows a typical drilling layout using a drone and 3D software at Heidelberg Material Union Plant

The design drilling pattern is sent the drills through the cloud. These drills are called smart drills. To improve accuracy of drilling and collected performance data, a retrofit was designed and installed on the existing old drills on site. The research method adopted was to make sure that GPS enable system on the drill allows for easily transfer of drilling pattern data to the drill so that they can drill the exact location of holes and collect samples as needed. While down the hole drills (DTHs) or rotary crushing drills are typically used for large-scale surface mining, percussion rock drills are the most widely utilized equipment for drilling in small-scale surface or underground mining scenarios. Figure 30 shows the drill used at the quarry for drilling and the sampling method adopted for the research work.



Active Drilling on Bench

Sampling tube for drill holes cutting

Drill holes cutting sample with labeling (Shot ID and Hole Number

Figure 30 shows the active drilling at the quarry on a bench and the sampling method used for the sample

3.2 Machine Learning Methods for CO2 Prediction

Algorithms that use models and inference based on data processing without the need for explicit instructions are referred to as machine learning algorithms [276]. Without being specifically taught to do so, machine learning algorithms create a mathematical model of sample data, or "training data," to generate predictions or choices. It's been regarded as an artificial intelligence subset. Finding patterns in big data sets to extract information and arrange it in a way that makes sense for later use is known as data mining [277]. According to Chakrabarti et al. [277], it includes parts of analysis, database administration, and data pre-processing, model and inference considerations, interestingness measures, complexity considerations, post-processing of structures found, visualization, and online updating. Essentially, we may create algorithms to extract data and identify significant hidden information from it using machine learning and data mining approaches. Prescriptive analytics looks for information that can assist in determining the appropriate course of action in a particular scenario, whereas predictive analytics looks for information that can forecast future events from data based on past trends.

As discussed in Chapter 2, numerous sectors are actively taking advantage of the novelty of utilizing machine learning techniques to anticipate CO_2. It was also observed that while the cement manufacturing business is using machine learning and artificial intelligence (AI) to correctly anticipate CO_2, this is not the case for the many studies referenced herein. The reasons behind the poor adoption of AI and machine learning in the concrete, aggregate, and cement industries are demonstrated by Boakye et al. [29] There is only one paper that discusses using machine learning to forecast CO_2 based on calcination that comes up in literature searches. Regretfully, the study is based on laboratory experimental data rather than industrial performance data. In addition to these well-known empirical procedures, Shen et al. [139] described other approaches used to estimate the quantity of CO_2 emission from cement. This study uses data from laboratories to forecast CO_2 emissions using machine learning. According to the paper, it is advised to test the models based on specific process data that depict both average and exceptional plant operating circumstances. As a result, more accurate models based on data from real plants will be created. To anticipate CO_2, the current work uses machine learning and artificial intelligence (AI) techniques to analyze historical real plant performance monitoring data from cement manufacturing. To improve understanding of CO_2 emission and forecast, this will demonstrate the necessity for the cement producing sectors to use cutting-edge technologies. The process flow model (Figure 31) illustrates the detailed system architecture for the machine learning (ML) predictive analytics research project about CO_2 calcination. Sensitivity analysis trains the algorithms using historical manufacturing health data from more than ten thousand input variables. The least squares method or the method of maximum likelihood are frequently used to determine the parameters of nonlinear regression models, just like linear regression models. When the error components have a normal distribution and a constant variance, the parameter estimates obtained from the two estimating processes are comparable. Unlike linear regression models, nonlinear regression models typically do not include mathematical expressions for the maximum likelihood and least squares estimators. Often, the only way to access these calculations is via linear regression. However, both estimating approaches need the use of laborious numerical search methods. As a result, standard computer software tools are typically used to evaluate nonlinear regression models. The following equation displays the nonlinear regression model that was used.

$$F_{C_t} = \alpha_1 \exp\left(b_1 \frac{NP_c}{C}\right) + \alpha_2 \exp\left(b_2 \frac{SF}{C}\right) + \alpha_1 \exp\left(b_3 \frac{NP_s}{C}\right)$$

Based on these data, a variety of regression models are examined and utilized to determine which independent factors in cement manufacturing had the most influence on the dependent variables, or which will have the lowest root mean squared error (RMSE). The accuracy of the proposed models was evaluated using the following metrics: RMSE, Eq. (11), the Durbin-Watson test (Eq. (12)), the F-test, the t-test, and something that determines coefficient (R2) (Eq. (10).

$$R^2 = 1 - \frac{\sum(residuals)^2}{\sum(Predicted - Values)^2}$$

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2}$$

The laboratory measurements and their corresponding estimated values using the proposed model are denoted by y and y, respectively, and N is the number of data sets. If used, a model with a lower RMSE would have higher predictive power and a lower overall error rate. To determine whether multi-collinearity is present, the Durbin-Watson statistic is applied. The middle number, 2, indicates that there is no connection between the entered variables in the Durbin-Watson distribution, which has magnitude values ranging from 0 to 4. A value of 1.5 to 2.5 is adequate to generate models devoid of multicollinearity. The following equation is used to calculate the Durbin-Watson, or DW, statistics.

$$DW = \frac{\sum_{t=2}^{T}(e_t - e_{t-1})}{\sum_{t=1}^{T} e_t^2}$$

Sensitivity analysis (SA) is a method for figuring out how variations in the input parameters affect a model or simulation's output's uncertainty. SA makes it easier to comprehend how changes in the input parameters affect a model's outputs. Determining which factors produce the highest variance in the output and measuring the model's sensitivity to changes in these parameters are especially helpful for complicated models. Additionally, by locating and eliminating sources of uncertainty in the input data, SA can help a model become more accurate. Sensitivity analysis is a crucial tool used in many branches of computational science to investigate the propagation of uncertainty through input-output interactions or to obtain insight into the mathematical model and the interplay of its parameters. One of the fundamental tenets of the most advanced sensitivity analysis techniques is broken in many instances by the stochastically dependent inputs. As a result, values that do not accurately represent the contributions of the input parameters are produced in the results that are obtained when the correlations are ignored. Sensitivity analysis allows users of mathematical and simulation models to examine how each model input influences the result and comprehend how the model output depends on the input. For this effort, Python coding analysis was chosen. The significance of the independent variables will also be evaluated to determine which one has the most effect on CO_2 emissions. The number of neurons and hidden layers in the Artificial Neural Network (ANN) model were selected at random. Figure 32 displays the layout of an ANN network that represents inputs and outputs. The neural network is composed of an artificial neural network. The circuit's incorporation of components that sense the neurons' biological similarities allows the trained neurons to identify solutions, make predictions, describe data, and even forecast what will happen in the future. Consequently, many applications were discovered in the simulation of exceedingly complex relationships and the modeling of many projections for concrete strength blends. On the other hand, a network of this kind usually consists of multiple layers with distinct sequential ordering, each of which has a set of neurons that are similarly connected to the neurons in the layer or layers above it. For the first and last layers, which are the input and output variables, we use the real input and output data. The hidden layers are viewed as multi-layered structures that alter the hidden data using the input data. Neuron weights can be changed to enhance task performance or network emulation using learning principles and neural networks, up until a system meets the emulation requirements or achieves its goals. In the case of neuron transfer functions, which are now called mathematical functions, the input-to-output transformation of each neuron is applied to the data. Because buried layer neurons frequently use the log-sigmoid transfer function, the back-propagation method proves to be especially helpful in this context. The hidden (transitional) and output layers need to go through two distinct stages to convert inputs into the appropriate outputs. To find a neuron's net input, one can multiply a constant factor by the total of its input and weight. The second stage is to create the product from the net input. In Figure 32, a new multi-layer feedforward neural network design is depicted. It has eight input neurons, six hidden neurons in the first layer, and four hidden neurons in the second layer. One output neuron is included. The multi-layered perceptron (MLP), a basic kind of neural network, consists of three layers of neurons: input, hidden, and output, together with forward information flows (Fig. 32). The resulting network, called feedforward backpropagation (FFBP), uses the steepest or gradient descent strategy to minimize the error value between the desired and realized outputs. In other words, the following equation states that the weight correction (W) is proportional to the rate of global error change (E) about that weight.

$$\Delta wa \frac{\partial E}{\partial w}$$

FFBP will provide an estimate of the number of hidden layers and the total number of nodes in the input and hidden layers after analyzing different network topologies. ANNs can be made to stop overfitting in a few different methods. Giustolisi and Laucelli [278] summarize these strategies.

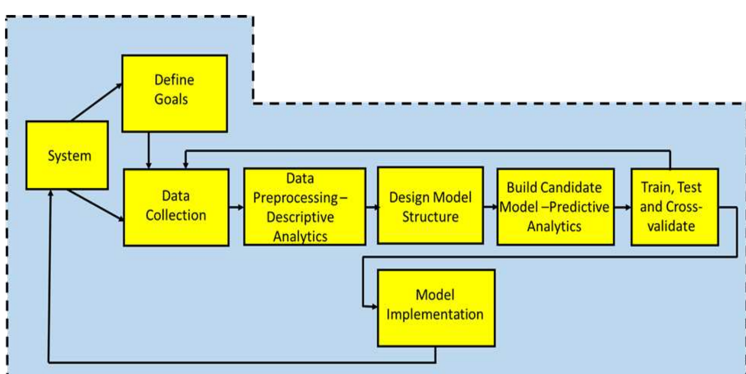


Figure 31. Predictive Modeling steps used for machine learning analytics [29]

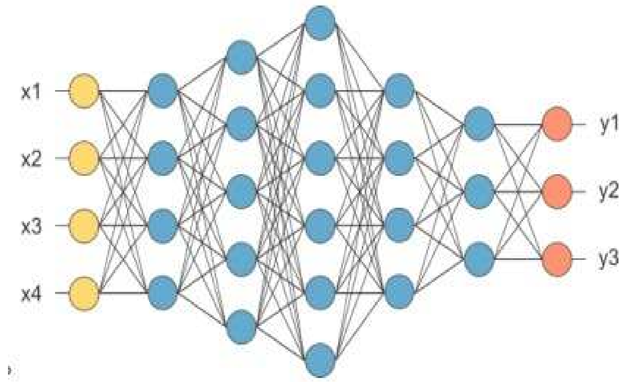


Figure 32. The Neural Network Architecture used for the machine learning analysis, where x1, x2, x3, and x4 are the input vector, and y1, y2, and y3 are the output vector. Between them are the hidden layers (five shown here).

3.2.1 Root Mean Square Error (RMSE) with Different Algorithms for the Predictive Modeling

Although RMSE is helpful in a variety of situations, regression analysis and model evaluation for numerical predictions are two areas in which it excels. The following justifies the extensive application of RMSE:

Measure of prediction error: The mean difference between the expected and actual values in the dataset is measured by RMSE. The difference between observed and model-predicted values is calculated. The mean squared prediction error is a single number that is obtained by applying the RMSE formula, which finds the square root of the mean squared errors.

Sensitivity to outliers: Anomalies in the data can affect the RMSE. Huge errors have a detrimental effect on the result since they must be squared. This sensitivity could be helpful in determining and comprehending the impact of extreme forecasts or outliers on the model's functionality.

Interpretability: The RMSE is easier to read and compare across datasets and models since it is provided in the same units as the predicted variable. If, for example, you are forecasting house values in dollars and the RMSE is also in dollars, you can assess the average prediction error in a pertinent and comprehensible manner.

Optimization criterion: Model training often employs RMSE as an optimization criterion. While fitting the model to the training set, a lot of machine learning algorithms try to reduce the RMSE. The model is forced to generate predictions that are as near to the real values as is practical by reducing the RMSE.

Comparison between models: It provides a standard measure to compare the efficacy of different models. When comparing various models or algorithms, RMSE can be used to assess which one predicts unknown data more precisely and with fewer prediction mistakes.

It's important to keep in mind that RMSE is not the only statistic used to evaluate models. Depending on the issue and context, additional metrics like precision and recall, the linear regression correlation coefficient R-squared, or Mean Absolute Error (MAE) may also be relevant. The many RMSRs chosen for the predictive modeling algorithms that compare the predicted with the true are as follows: (1) Linear Regression; (2) Lasso Regression; (4) Decision Tree Regressor; and (5) Random Forest Regressor. The process of machine learning modeling involves several different tasks, from gathering raw data to putting learning algorithms into practice. The analysis workflow of suggested machine learning approaches is depicted in Figure 33. Machine learning workflows define which phases are implemented during a machine learning project. The typical stages involve data collection, data pre-processing, dataset construction, model training and refinement, evaluation, and deployment to production. While all phases are integral, the data pre-processing stage is particularly significant due to its role in enhancing data quality and ensuring that the data is well-suited for subsequent analysis and modeling.

The effectiveness of machine learning models heavily relies on the quality and suitability of the input data. During the data pre-processing phase, the raw data is cleaned, transformed, and prepared for analysis. This preparation significantly enhances the model's performance by addressing data inconsistencies, outliers, and missing values.

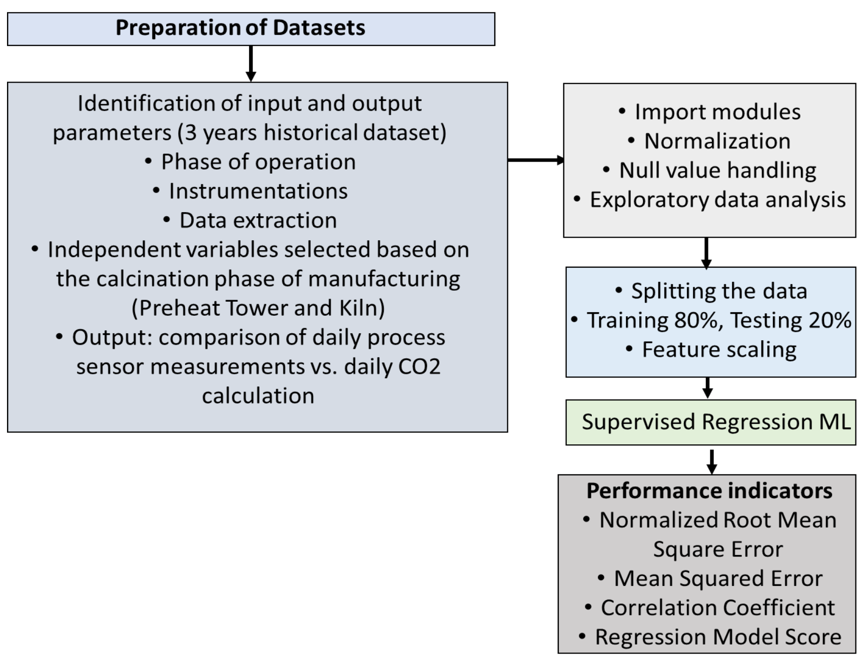


Figure 33 shows the workflow used for the ML

3.2.2 Data Characterization and Challenges of "Big Data"

The input is made up of several variables that are noted in the plant's daily log sheet, including draught, tertiary air, preheater outlet gas temperature, fan speed, kiln feed, and other related variables. During a cement production plant's three years of continuous operation, raw data was gathered. The features that were chosen typically matched the operation of a calciner, kiln, and preheat tower. A large enough dataset was created to aid in the detection of anomalies and improve the model's accuracy. The heat map correlation of the dataset was plotted to acquire a measure of the correlation between the characteristics and the label. The other features were removed from the feature set, and only those that showed a strong correlation with the label were kept. As Figure 33 has already indicated, the dataset was split into training, validation, and testing datasets. A portion of plant data also relates to malfunctions or unusual operation. Thus, the dataset began to contain a variety of outliers and missing data points. The dataset was statistically distorted due to these outliers and missing data points, which in turn made the forecast inaccurate. To assess performance, sensors and instruments should preferably be placed alongside assets. Analog to digital conversion creates a data set that is stored. After that, these digital data can be kept monitoring performance patterns in real time, upon which judgments can be made. For a thorough production planning and control on a Siemens system, the entire sensor networks for the calcination process occurring inside the production process in the kiln and preheat tower are taken into consideration. Figure 34 demonstrates a typical digitization workflow process for cement production plants including Programmable Logic Controllers (PLC). Multiple sensors were installed to reduce errors in the data.

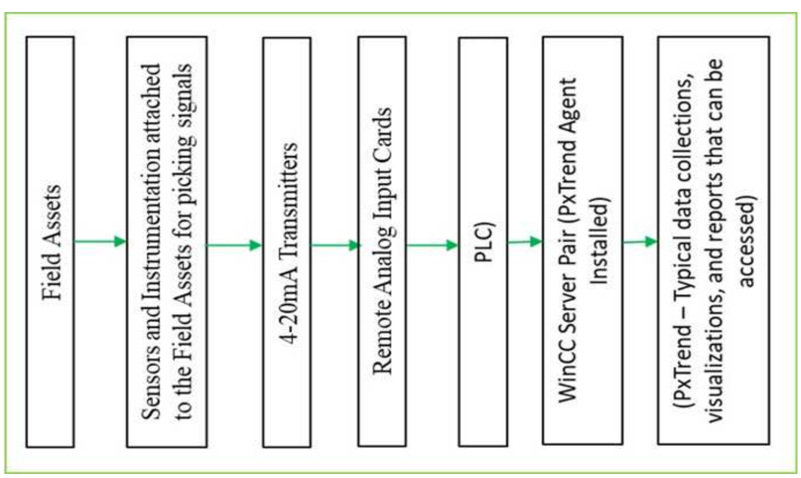


Figure 34 Typical instrumentation data system and data collection setup for Heidelberg Material Union Bridge Cement Plant [29]

The independent variables in cement manufacture were selected because they are all performance tracking instrumentation sensors associated to the calcination process phases with the kiln and preheat tower, which most likely contributed to CO_2 creation. The data were all normalized prior to being entered into the models.

3.3 Data Collection Limitation

The data featured in this study can be obtained upon request from the corresponding author. However, the data are not accessible to the public as they are subject to the data protection policy of Heidelberg Material manufacturing.

It important to note that the data used for the are only related to the quarry operation, preheat tower and kiln of the cement manufacturing operation at Heidelberg Material Union Bridge Plant. Therefore, any results obtained due to analysis of these dataset is pertaining to only this operation. The hope of this novelty is that this becomes replicable at other system plants to help reduce cement manufacturing impact on the environment, social and political aspect of society.

While this chapter primarily outlines the materials and methods employed, the subsequent chapters will delve into the quantitative results derived from the analysis of the datasets. These results will provide a comprehensive understanding of the environmental, social, and political implications of the cement manufacturing process at Heidelberg Material Union Bridge Plant.

Chapter 4 – Research Results

This chapter describes the outcomes that were obtained using the approach outlined in Chapter 3. This article evaluates the effects of controlling raw material supply to the kiln using modified versions of already available computer software modeling tools and data management control architecture. The effects on overburden removal, sand consumption reduction, and kiln feed quality are assessed using a statistical analysis of process capabilities. The impact of the step adjustments on quality was determined by statistically comparing the quarry's 2019 and 2020 chemical data. Because updated mining software (Surpac) was used, mining was able to achieve optimum land usage with minimal disturbance and reduce overburden squandering to minimize footprint impact. The data for critical chemistry targets used to assess the quality of material from the quarry, raw mill, and kiln feeds were compared using a process capability analysis. The effect of the control loop systems installed in the quarry and raw mill in 2020 on quality is discussed in this section.

Feature correlation heat maps were initially employed to reduce the size of our study by identifying possible correlations and removing factors that had little to no bearing on CO_2 generation (dimensionality reduction). Next, utilizing the string potential correlation input variables, predictive models were created. Furthermore, findings from predictive models are also provided here. Sensitivity analysis made use of over 60 independent input variables with over 50,000 data points. To evaluate and train the model's quality, the dataset was split 80/20. The model's utilization of crucial industrial sensors in comparison to daily CO_2 computations was one of its limitations. Since the model only compares industrial processes with sensors, CO_2 creation likely comes from other, unmeasured sources. Furthermore, although generally dependable, sensor readings may add a certain amount of measurement error. However, the outcomes generally show a high degree of dataset reliability. Because they are all performance-tracking instrumentation sensors connected to the calcination process phases with the preheat tower and kiln, which most likely contributed to CO_2 generation, the independent variables in cement manufacturing were chosen.

4.1 Raw Material Optimization and Wasting

This research evaluates the effects of controlling raw material supply to the kiln using modified versions of already available computer software modeling tools and data management control architecture. The effects on overburden removal, sand consumption reduction, and kiln feed quality are assessed using a statistical analysis of process capabilities. Stable processes under statistical control are assessed as Cp, Cpk, and Ppk in process capacity analysis. where the following equations are used to evaluate Cp, Cpk, and Ppk:

$$Cp = \frac{(USL - LSL)}{(6\sigma)}$$

$$Cpk = min \frac{(USL - \mu,\ \mu - LSL)}{(3\sigma within)}$$

$$Ppk = min \frac{(USL - \mu,\ \mu - LSL)}{(3\sigma\ overall)}$$

Because sigma and the sample standard deviation will be the same, the values for Cpk and Ppk will converge to almost the same value. Stated differently, the process is probably in statistical control if Cpk is extremely near to Ppk. There is less process variability, and the process is well-controlled within targets when the Cpk is closer to or larger than 1. This demonstrates process optimization and consistency as well.

4.1.1 Reduction of raw material (sand) in the raw material mix and its impact

In developing nations, sand mining is illegal, which benefits the so-called “sand mafia” that uses many illegal ways to obtain it. Utilizing technology and creative data management controls contributes to a decrease in the consumption of raw materials, particularly sand. A controlled addition of waste material, such as shale, can help replace the use of sand that is contracted out. In comparison to 2019, clinker production rose in 2020. In typical circumstances, sand usage ought to rise by 4% for every clinker produced. In 2020, the percentage of clinker production basis that used sand was 9.6%, as opposed to 10.2% in previous years. This indicates a 6.3% reduction in the amount of sand used at the raw mill and quarry because of using a closely regulated mix in the quarry [12]. This finding indicates that cutting back on the usage of raw materials can be achieved through the application of cutting-edge technology, creativity, and a data management control loop system. To facilitate process optimization and improvement, the cement industry needs to embrace new technologies and data analytics tools. In addition to enhancing operations, these optimization techniques will have a big environmental impact by reducing the need for illegal sand mining along beaches which causes land degradation and, in some places, increases wave destruction of buildings along the coast. In addition, the cost of raw materials can be reduced.

4.1.2 Reduction of raw overburden removal and its impact on the environment

The mining sequence of the quarry operation can be precisely planned thanks to the mining plan created using adapted 3D software. It makes precision mining possible and prevents the over-mining of overburden debris, which results in environmentally harmful stockpiles. The models make it possible to precisely manage the amount of overburden that must be removed to expose the specific amount of dolomite and limestone that is needed. Furthermore, by using predictive modeling enabled by the software, some of the overburden material can be added to the quarry material mix for the manufacturing of clinker. The sole drawback is that shale, the overburden material, is a source of high alkalinity, which can readily impact clinker quality and, in turn, cement quality. As a result, it must be carefully managed within the given chemistry target. Because of the quarry's data management architecture, overburden waste was able to be used in the mix, resulting in an annual reduction of over 150,000 metric tons. The fact that more than 1.5 million metric tons of material can be used over ten years as opposed to being squandered otherwise as waste dumps covering massive land areas will harm the environment. This is a positive influence on the environment.

4.1.3 Analysis showing improvement in quality due to quarry control mix feedback

This section of the chapter covers the analysis of how quality was improved using the methodology deployed for this research work. Lime Saturation Factor (LSF), Silica Moduli (SM), Alumina Moduli (AM), concentrations of dicalcium silicate or belite (C2S), tricalcium silicate or alite (C3S), tricalcium aluminate (C3A), and tetracalcium aluminoferrite (C4AF) are the parameters that determine the quality of clinker. The quality of the limestone mix at the quarry has a major impact on the quality of the clinker. It is important to note that the impact of the methodology adopted to optimize the raw material at the quarry must have a positive impact on the quality of the clinker produced. To validate the impact, the following statistical analysis results were performed and presented herein to show that even though a new novel idea was implanted to improve raw material optimization and overburden wasting volume, the quality of raw material and clinker was never compromised. These results will validate that the process can be adopted and replicated for other cement quarries without any negative impact on the clinker quality, which is an extremely important factor in structure integrity during construction and for meeting customer's needs.

4.1.3.1 Process Capability Analysis of Quarry Quality Data

For uniformity, the amount of MgO in the quarry mix needs to be managed. To prevent variability in MgO in the quarry mix, there needs to be greater process control and a reduced standard deviation. This is because inconsistent operations might lead to liquid development in the kiln, which can cause damage. The results of the process capability data analysis for MgO in the quarry mix for 2019 and 2020 are displayed in Table 5 and Figure 35. The standard deviation in 2020 was improved by 15% because of the control loop. Additionally, there was a 5% improvement in the Cpk, a reliable metric of process control. There is less process variability, and the process is well-controlled within targets when the Cpk is closer to 1 or larger than 1. This demonstrates process optimization and consistency as well.

Table 5 The process capability analysis data result for MgO within Quarry mix material for 2019 vs. 2020

	Process Data		Overall Capability Results		
	2019	2020		2019	2020
LSL	2	2	Pp	0.37	0.42
Target	3	3	PPL	0.27	0.47
USL	4	4	PPU	0.46	0.37
Sample Mean	2.75	3.12	Ppk	0.27	0.37
Sample N	1087	759	Cpm	0.35	0.41
StDev (σ) (Overall)	0.912	0.795			
StDev (σ) (Within)	0.782	0.786			
			Potential Capability Results		
				2019	2020
			Cp	0.46	0.42
			CPL	0.35	0.48
			CPU	0.58	0.37
			Cpk	0.35	0.37

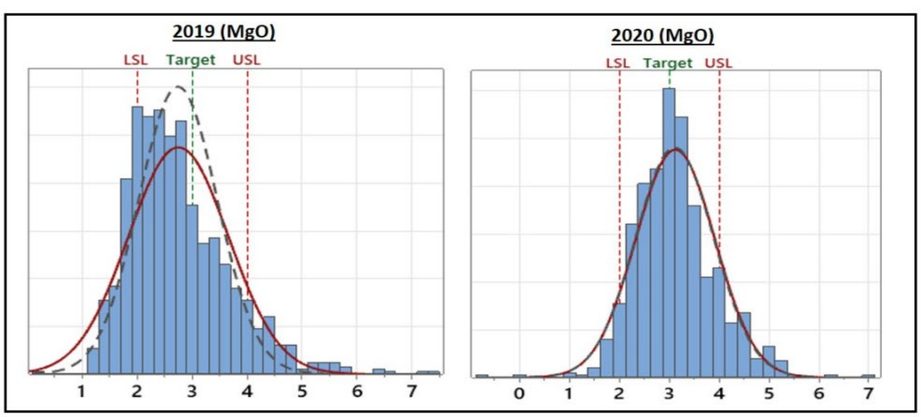


Figure 35 shows the normal distribution of MgO data for 2019 vs 2020

Shale, which is the source of K2O and a measure of the impact of alkalinity in the quarry mix, was also evaluated. Table 6 and Figure 36 show the output of the process capability data analysis for K2O within the quarry mix for 2019 and 2020. The control loop had an impact, improving the standard deviation in 2020 by 49%. Also, the Cpk, a good indicator for process control, is improved by 267%. These improvements signify a reduction in variability within the process, indicating enhanced process control and stability.

Table 6 The process capability analysis data result for K2O within Quarry mix material for 2019 vs. 2020

	Process Data		Overall Capability Results		
	2019	2020		2019	2020
LSL	0.31	0.31	Pp	0.17	0.26
Target	0.34	0.38	PPL	0.45	0.55
USL	0.45	0.45	PPU	-0.11	-0.03
Sample Mean	0.49	0.45	Ppk	-0.11	-0.03
Sample N	1083	759	Cpm	0.13	0.19
StDev (σ)(Overall)	0.135	0.091			
StDev (σ) (Within)	0.128	0.087			
			Potential Capability Results		
				2019	2020
			Cp	0.18	0.27
			CPL	0.48	0.57
			CPU	-0.11	-0.03
			Cpk	-0.11	-0.03

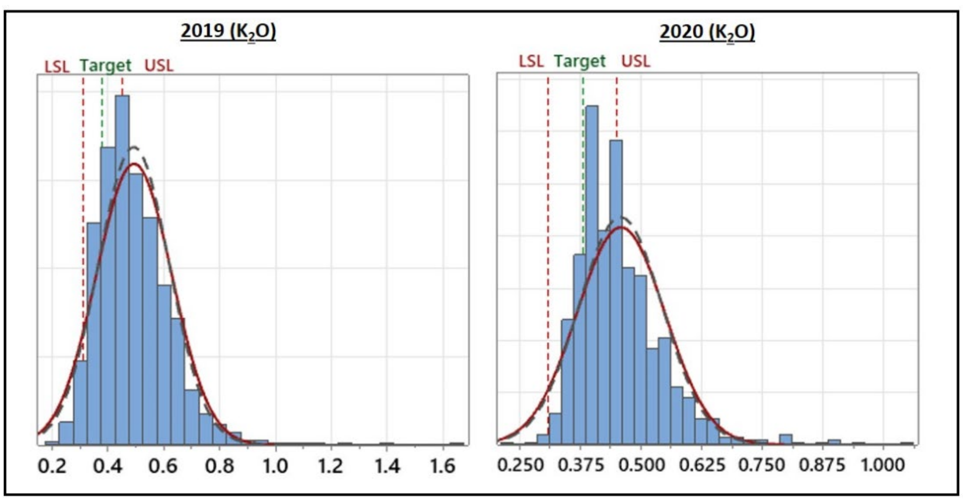


Figure 36 shows the normal distribution of K2O data for 2019 vs 2020

4.1.3.2 Process Capability Analysis of Raw Meal Quality Data

NaEQ data should be taken into consideration to quantify the effect of alkalinity on the raw mill. The results of the process capability data analysis for NaEQ inside the raw mill throughput into the blending silo for 2019 and

2020 are displayed in Table 7 and Figure 37. The 2020 standard deviation was improved by 101% as a result of the control loop. A 34% improvement is seen in the Cpk, a useful process control measure.

Table 7. The process capability analysis data result for NaEQ within raw mill output material for 2019 vs. 2020

	Process Data		Overall Capability Results		
	2019	2020		2019	2020
LSL	0.30	0.30	Pp	0.37	0.74
Target	0.35	0.35	PPL	0.17	0.38
USL	0.40	0.40	PPU	0.56	1.10
Sample Mean	0.32	0.33	Ppk	0.17	0.38
Sample N	5642	4709	Cpm	0.32	0.50
StDev (σ)(Overall)	0.045	0.023			
StDev (σ) (Within)	0.015	0.011			
			Potential Capability Results		
				2019	2020
			Cp	1.13	1.58
			CPL	0.53	0.80
			CPU	1.73	2.35
			Cpk	0.53	0.80

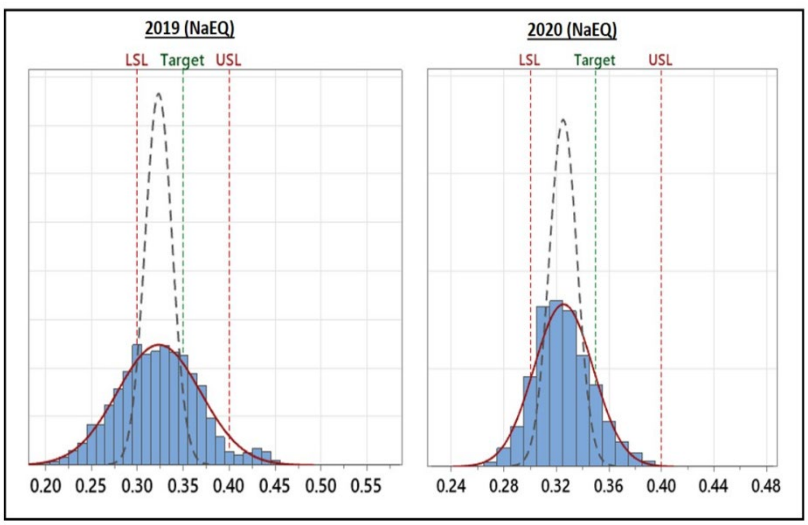


Figure 37 shows the normal distribution of NaEQ data for 2019 vs 2020

MgO data must be taken into consideration to quantify the effect of liquid production in the kiln. The results of the process capability data analysis for MgO inside the raw mill throughput for the blending silo for 2019 and 2020 are displayed in Table 8 and Figure 38. The 2020 standard deviation was reduced by 46.5% because of the control loop. A 233% improvement is seen in the Cpk, a useful process control metric.

Table 8. The process capability analysis data result for MgO within raw mill output material for 2019 vs. 2020

	Process Data			Overall Capability Results	
	2019	2020		2019	2020
LSL	1.95	1.95	Pp	0.10	0.33
Target	2.10	2.1	PPL	-0.16	0.25
USL	2.25	2.25	PPU	0.37	0.41
Sample Mean	1.72	2.06	Ppk	-0.16	0.25
Sample N	5642	4709	Cpm	0.08	0.32
StDev (σ)(Overall)	0.480	0.152			
StDev (σ) (Within)	0.065	0.043			
				Potential Capability Results	
				2019	2020
			Cp	0.77	1.17
			CPL	-1.18	0.89
			CPU	2.71	1.46
			Cpk	-1.18	0.89

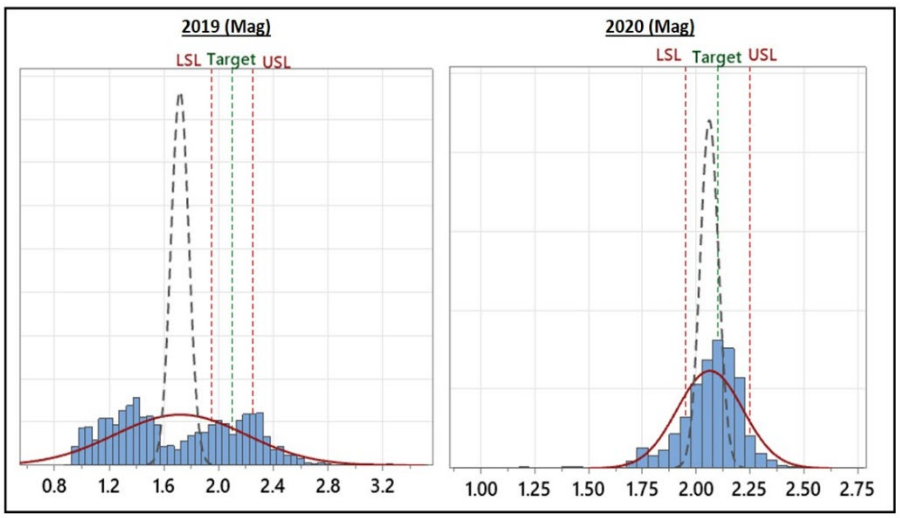


Figure 38 shows the normal distribution of MgO data for 2019 vs 2020

4.1.3.3 Process Capability Analysis of Kiln Feed Quality Data

To measure the impact of alkalinity on the kiln feed coming from the blending silo, the data to be considered is NaEQ. The results of the process capability data analysis for NaEQ within the Kiln Feed from the blending silo into the Kiln for 2019 and 2020 are displayed in Table 9 and Figure 39. The standard deviation in 2020 was improved by 53% because of the control loop. A 20% improvement is made to the Cpk, which is a useful process control indicator. This is significant in the quality of clinker production.

Table 9. The process capability analysis data result for NaEQ within Kiln Feed material for 2019 vs. 2020

	Process Data		Overall Capability Results		
	2019	2020		2019	2020
LSL	0.30	0.30	Pp	0.42	0.65
Target	0.35	0.35	PPL	0.36	0.57
USL	0.40	0.40	PPU	0.48	0.72
Sample Mean	0.34	0.34	P_{pk}	0.36	0.57
Sample N	8222	6912	C_{pm}	0.42	0.63
StDev (σ)(Overall)	0.039	0.026			
StDev (σ) (Within)	0.009	0.008			
			Potential Capability Results		
				2019	2020
			Cp	1.81	2.19
			CPL	1.56	1.94
			CPU	2.06	2.44
			Cpk	1.56	1.94

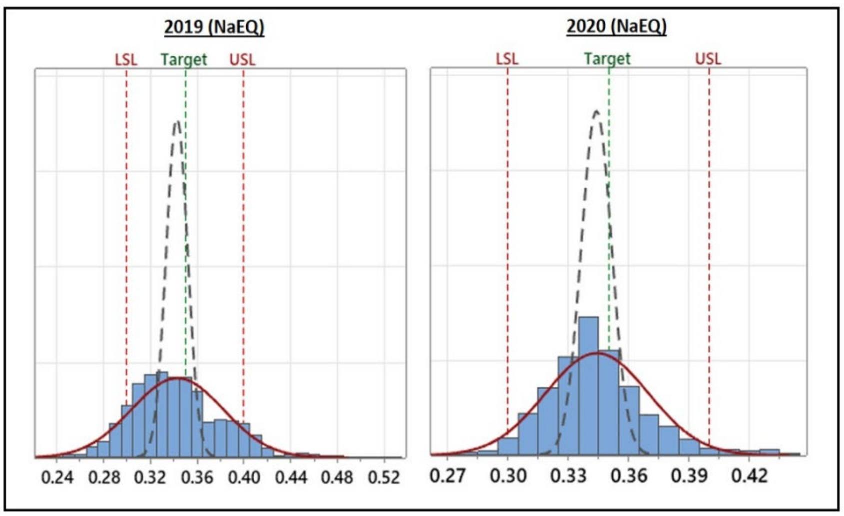


Figure 39 shows the normal distribution of NaEQ data for 2019 vs 2020

Table 10 and Figure 40 show the output of the process capability data analysis for MgO within the quarry mix for 2019 and 2020. The control loop had an impact, improving the standard deviation in 2020 by 248%. Also, the Cpk, a good indicator for process control, is improved by 139%. This is significant in the quality of clinker production.

Table 10. The process capability analysis data result for MgO within Kiln Feed material for 2019 vs. 2020

	Process Data		Overall Capability Results		
	2019	2020		2019	2020
LSL	1.95	1.95	Pp	0.11	0.39
Target	2.10	2.1	PPL	-0.11	0.32
USL	2.25	2.25	PPU	0.33	0.47

Sample Mean	1.81	2.07	Ppk	-0.11	0.32
Sample N	8222	6912	Cpm	0.09	0.38
StDev(Overall)	0.441	0.127			
StDev (Within)	0.061	0.020			
			Potential Capability Results		
				2019	2020
			Cp	0.82	2.51
			CPL	-0.78	2.00
			CPU	2.42	3.01
			Cpk	-0.78	2.00

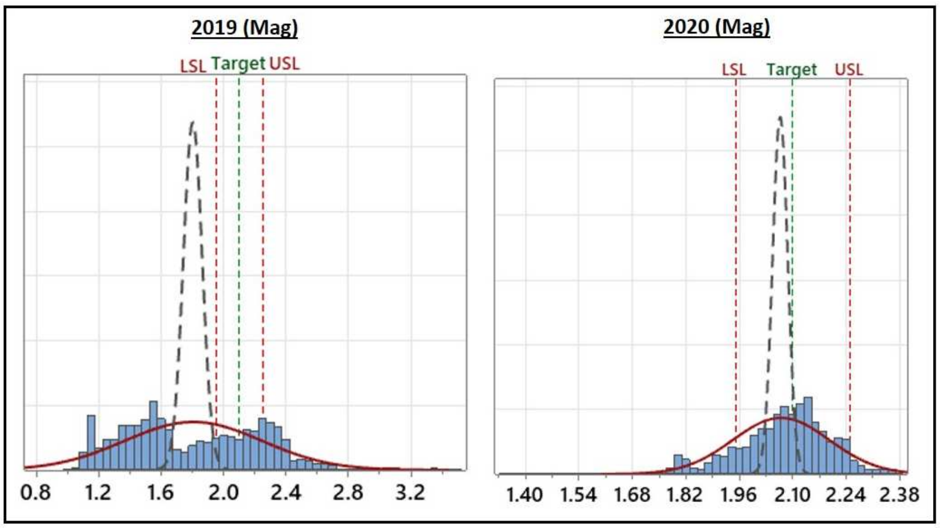


Figure 40 shows the normal distribution of MgO data for 2019 vs 2020

The results of the process capability data analysis for LSF within the kiln feed from the blending silo for 2019 and 2020 are displayed in Table 11 and Figure 41. The 2020 standard deviation improved by 45% because of the control loop. Additionally, there is a 65% improvement in the Cpk, a useful process control measure. This has an impact on the production of clinker quality. LSF plays a crucial role in determining the kiln feed's consistency and how that affects the quality of the clinker.

Table 11. The process capability analysis data result for LSF within kiln feed material for 2019 vs. 2020

	Process Data		Overall Capability Results		
	2019	2020		2019	2020
LSL	101.0	101.0	Pp	0.18	0.25
Target	102.0	102.0	PPL	0.07	0.19
USL	103.5	103.5	PPU	0.28	0.32
Sample Mean	101.5	101.92	Ppk	0.07	0.19
Sample N	8228	6913	Cpm	0.14	0.20
StDev(Overall)	2.366	1.637			
StDev (Within)	1.498	0.991			

	Potential Capability Results	
	2019	2020
Cp	0.28	0.42
CPL	0.11	0.31
CPU	0.45	0.53
Cpk	0.11	0.31

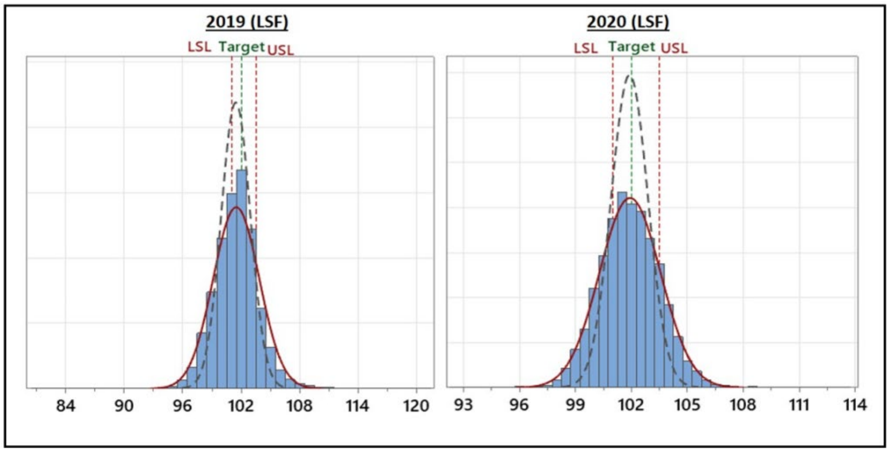


Figure 41 shows the normal distribution of LSF data for 2019 vs 2020

4.2 CO_2 prediction using machine learning

CO_2 emission predictions can be made using machine learning (ML) techniques. Decisions on operations and policy can be influenced by these forecasts. This makes the accurate forecast of carbon emissions in this kind of scenario one of the most significant and difficult scientific projects. As noted in Chapter 3, the study of complex, dynamic environmental phenomena with significant variability in time, space, and other parameters is increasingly being done with machine learning methodologies. This research paper introduces machine learning algorithms that use cement manufacturing characteristics during the calcination process to estimate CO_2 emissions.

4.2.1 Preheat Tower Data Analysis

To better understand how the process variables impact the emission of CO_2, using predictive tools were adopted. The Python analysis's findings are presented here. For the sensitivity analysis against CO_2, 31 independent preheating input variables with a total of over 31,465 data points were used. This analysis's data set spans the operations from October 23, 2022, to January 1, 2020. The statistical analysis of the dataset is displayed in Table 12. A sample Python code for the heat map model is shown in Figure 42.

Table 12 shows the statistical breakdown of the primary correlated value and corresponding CO_2 value for the sensitivity and predictive modeling

Statistics	V2: Stage 3 Cyclone Gas Outlet Temp	CO2 Generation
Mean μ	625.709	3271.366
Mean μ *(normalized)*	0.847	0.823
St. Dev. δ *(normalized)*	0.264	0.292
Variance δ^2 *(normalized)*	0.070	0.085

First, by identifying possible correlations and removing variables that had little to no bearing on CO_2 generation, feature correlation heat maps were utilized to focus our investigation. The two cement manufacturing methods had the strongest connections, according to the data sets that were performed. The heat map of the conducted sensitivity analysis is displayed in Figure 43. Comparable Python code was employed in the analysis. Heat map of the local sensitivity analysis results for the final model using historical data from the preheat tower system's manufacturing real-time instrumentation process as input variables compared to CO_2 output data. It displays the sensitivity indices of the most critical parameters across the preheater system for the cement manufacturing process metrics. Sensitivity indices show how altering parameter values relatively affects the measure. Deep blue indicates a positive correlation between the parameter and lighter blue indicates a negative correlation. The color intensity in each panel corresponds to the extent of the parameter sensitivity. The heat map variables are described in Table 13.

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

data = pd.read_excel("C:\Data\CombinedCementData.xls")

req_col_names = ["V1", "V2", "V3", "V4","V5", "V6", "V7", "V8", "V9",
                 "V10", "Calcination CO2"]
curr_col_names = list(data.columns)

mapper = {}
for i, name in enumerate(curr_col_names):
    mapper[name] = req_col_names[i]

data = data.rename(columns=mapper)

corr = data.corr()

plt.figure(figsize=(9,7))
sns.heatmap(corr, annot=True, cmap='Blues')
b, t = plt.ylim()
plt.ylim(b+0.5, t-0.5)
plt.title("Feature Correlation Heatmap")
plt.show()

X = data.iloc[:,:-1]         # Features - All columns but last
y = data.iloc[:,-1]          # Target - Last Column
```

Figure 42 displays the Python code used for the heat map

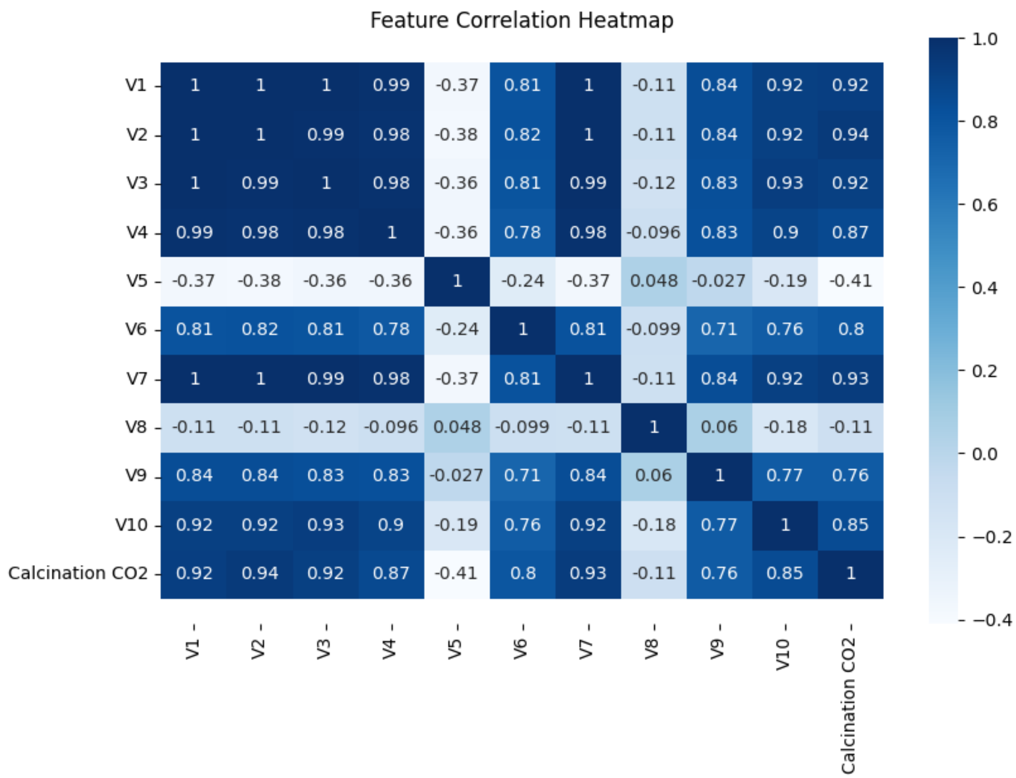


Figure 43 shows the heat map of the sensitivity analysis using input variables against CO_2 as the output variable

Table 13 shows the heat map of the sensitivity analysis using input variables against CO^2 as the output variable

Variable	Description
v1	Preheat.stg.2 cyclone gas outlet temp. [0 - 800 [°c]]
v2	Preheat.stg.3 cyclone gas outlet temp. [0 - 900 [°c]]
v3	Preheat cyclone 1a meal temp.to stage 3 [0 - 600 [°c]]
v4	Preheat cyclone 1b meal temp.to stage 3 [0 - 600 [°c]]
v5	Preheat.stg.4 cyclone cone pressure [-50 - 5 [mbar]]
v6	Preheat.stg.4 cyclone gas outlet temp. [0 - 1000 [°c]]
v7	Preheat cyclone 2 meal temp.to stage 4 [0 - 800 [°c]]
v8	Preheat.stg.5 cyclone cone pressure [-50 - 5 [mbar]]
v9	Calciner burner liner temp. east [0 - 1370 [°c]]
v10	Preheat. south loop duct level 170 temp [0 - 1370 [°c]]

Analyze the quantitative survey data to identify noteworthy patterns, trends, or associations among the variables. The correlation is shown in Figure 44. Figure 45 shows the PREHEAT.STG.3 CYCLONE GAS OUTLET TEMP. [0 - 900 [°C]]as the variable which has the highest correlation R^2 with the CO_2.

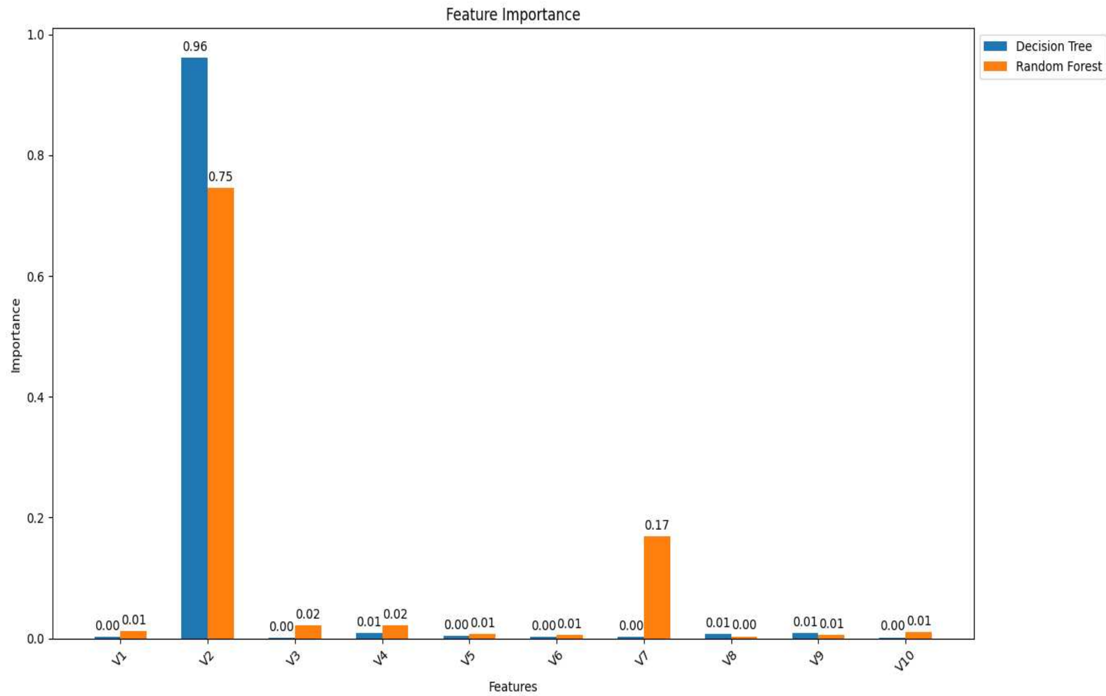


Figure 44 shows the most highly correlated variable with CO_2

The dataset was used to train five categories of regression models. The model with the lowest RMSE for each category was chosen to forecast the three outcome variables of apparent calcination degree and CO_2 molar fraction. Also displayed are the ANNmodel outcomes. To demonstrate how the conventional linear regression method differs from other approaches, the results of the linear regression classical model versus other models. Figure 45 below shows the predictive modeling of the dataset using multiple regression analysis. The results are represented herein. A scatter plot of the residuals vs. projected values or the observed vs. anticipated values, which is a basic regression data output from most statistical software, can be used to easily verify linearity. Points distributed in a straight line with a slope pattern and a generally constant variance (distance from the line) should be displayed in scatter plots. The scatter plot's bent pattern suggests that the basic slope-intercept model could use some work. To account for nonlinear linkages, the analyst must modify the model if nonlinear traits are noticed. A nonlinear transformation, such as a logarithmic transformation, could be applied by the analyst to the independent or dependent variables. Squaring the independent variable (i.e., adding x and x2 to the regression model) is one way to add an extra regressor that is a function of the original. In some circumstances, piecewise linear regression is an additional strategy.

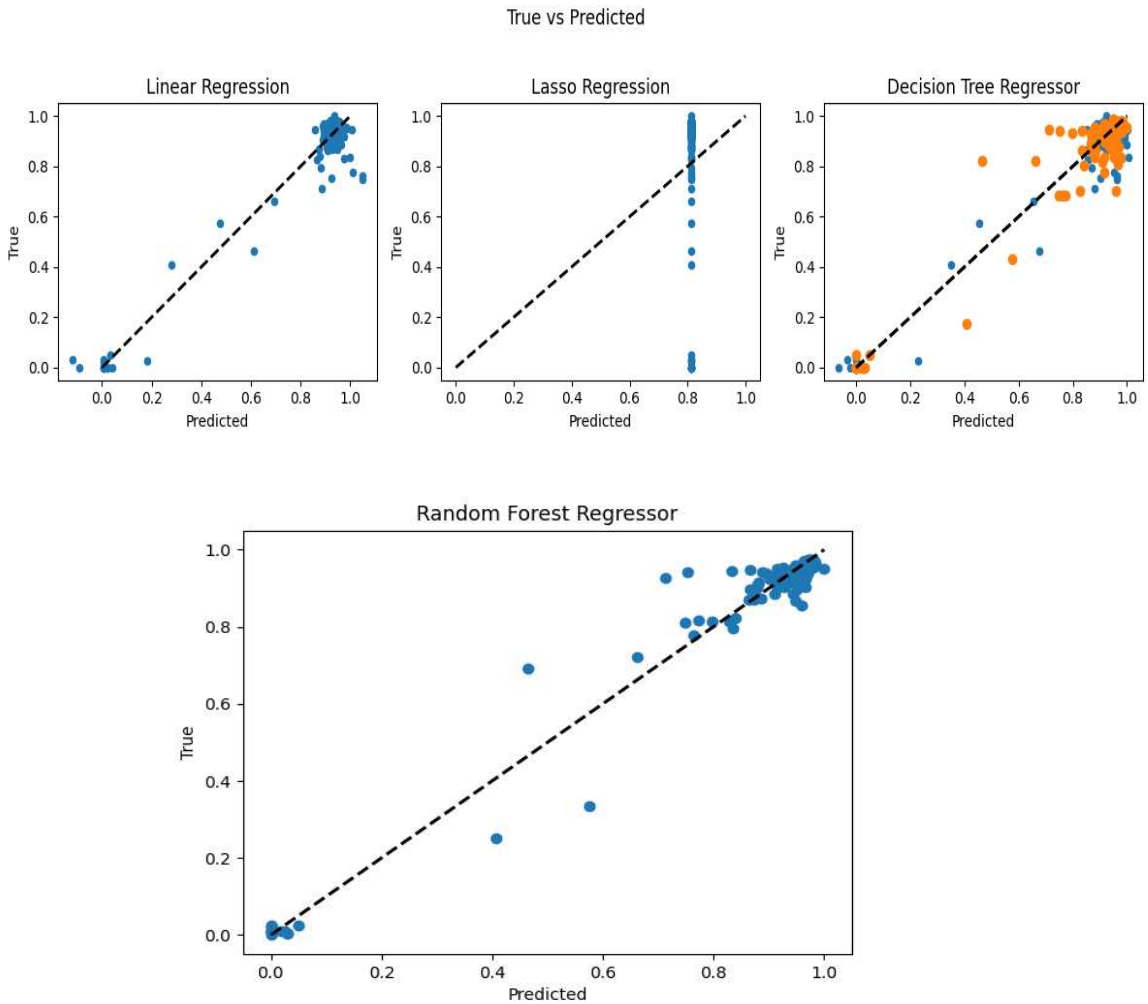


Figure 45 shows the various predictive models

The Root Mean Square Error (RMSE), often known as root mean square deviation, is a widely employed method for assessing the accuracy of predictions. It measures the Euclidean distance between predictions and the observed true values. The RMSE indicator illustrates how widely distributed these residuals are by demonstrating how closely the collected data is clustered around the projected values. Because the model has less error, the RMSE lowers as the data points move closer to the regression line. All the regression models' RMSEs linear, ridge, choice, and random are equal to or less than 0.05, except for the Lasso regression model, which has an RMSE of 0.24. Lower RMSE values indicate a model with less error and therefore more accurate predictions. RMSE values span from zero to positive infinity and are expressed in the same units as the dependent (outcome) variable. The RMSE for several predictive modeling techniques is displayed in Figure 46.

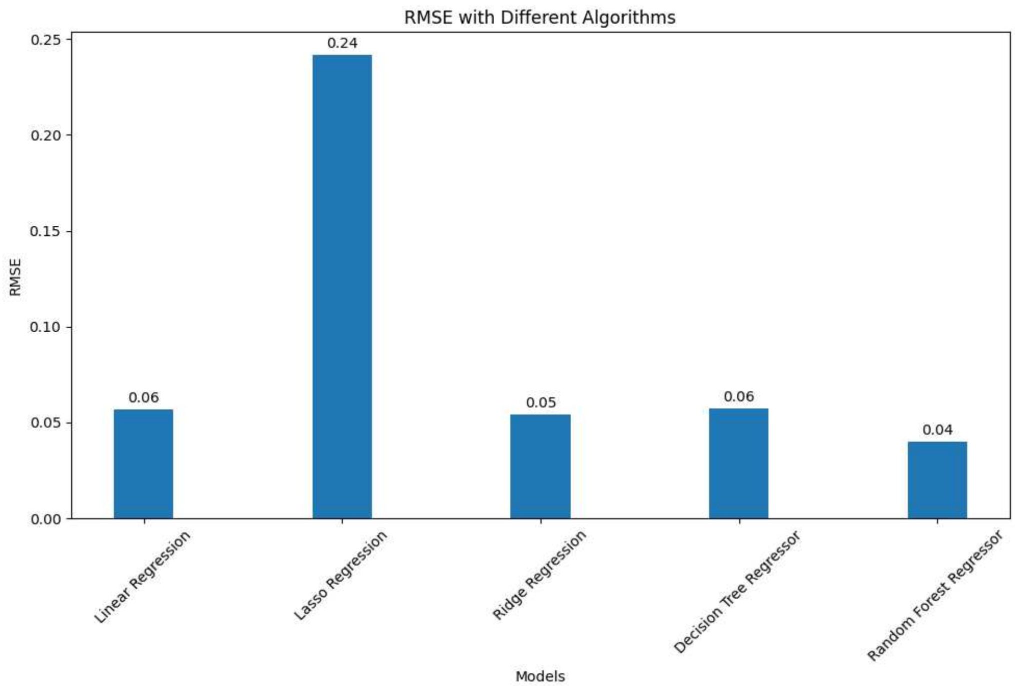


Figure 46 The Normalized RMSE with different Algorithms for the predictive modeling

4.2.2 Kiln Data Analysis

As discussed within the context of this paper, the culminating phase of the calcination process takes place in the kiln. The dataset employed for this analysis encompasses information from the kiln inlet, throughout the kiln, and up to the kiln outlet. The dataset comprises of the rotary kiln inlet O_2 of about 6.39% with oxygen 3106 PPMsw. The temperature ranges from 1100oC at the Kiln inlet to 1600^{oC} at the burning zone of the kiln. The rate of gas flow within the kiln dictates the speed at which fuel combusts and the duration that solids remain within the kiln. In calciner systems with tertiary airflow, the calculated gas duration ranges from 1.4 to 1.7 seconds to 4 to 5 seconds in total or hybrid flow systems, depending on the size of the kiln. This dataset can be gathered since the kiln system has several instrumentation systems installed for process control and monitoring. A dataset is created by compiling the data from these monitoring devices, which measure phenomena such as gas temperatures, pressure drops, material temperatures, fuel flow, heat inputs, kiln feed rate, clinker production rate, drivers' power, oxygen flow, etc. For this investigation, the dataset was taken out of the historical database. Take note that several control loops are used to oversee the production process. A kiln is a multivariable process that involves complex interactions between its different components. It has substantial nonlinearities, is more linked, and is frequently disturbed. For this study, the dataset including all the complex variables is retrieved and put into Excel format.

Since there is no calcination process occurring during the cooling, the cooler is not included in this data set. For the sensitivity analysis against CO_2, 21 independent kiln input variables with a total of over 21,315 data points were used. This analysis's data set spans the operations from October 23, 2022, to January 1, 2020. The Python analysis's findings are presented here. The statistical analysis of the dataset is displayed in Table 14.

Table 14 shows the statistical breakdown of the primary correlated value and corresponding CO_2 value for the sensitivity and predictive model

Statistics	V15: Kiln Main Drive Speed Control	CO_2 Generation
M	3.930	3271.366
μ (normalized)	0.862	0.823
δ (normalized)	0.305	0.292
δ^2 (normalized)	0.093	0.085

The data sets run showed the strongest correlations among the cement manufacturing process. Figure 47 shows the heat map of the sensitivity analysis performed, providing data visualization of the correlation of these manufacturing processes to the calculated generation of CO_2 for the process. A heatmap representing the outcomes of the local sensitivity analysis for the final model utilizing historical real-time instrumentation data from the entire kiln system as input variables, contrasted with the output data for CO_2. As depicted by the feature correlation heatmap below, V15 (Kiln Main Drive Control Speed) had the highest correlation with the amount of CO_2 generated during the final stage of the calcination process. Table 15 shows the variables' description of the heat map.

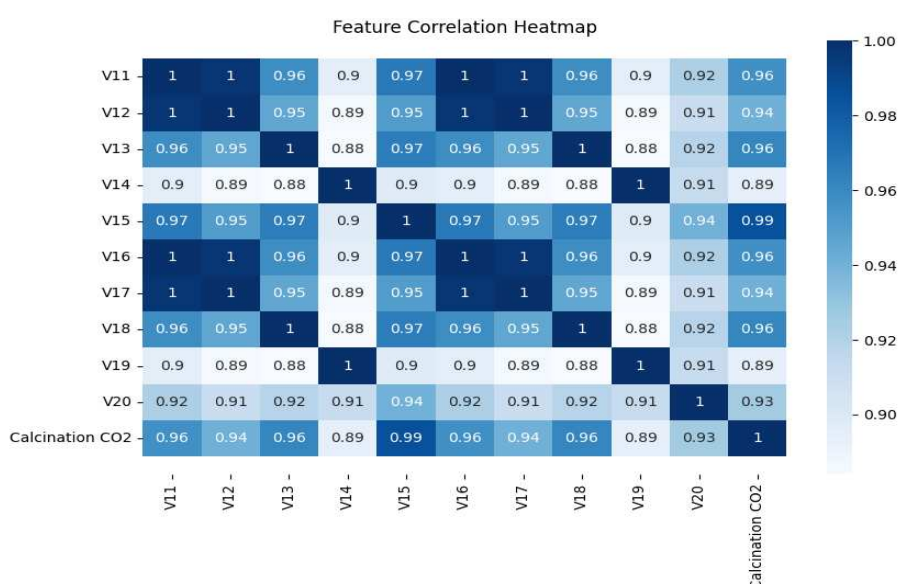


Figure 47 shows the heat map of the Kiln Process data sensitivity analysis

Table 15 lists the kiln process descriptions for each variable

Variable	Description
v11	Kiln main drive current [0 - 217 [a]]
v12	Kiln main drive torque [0 - 150 [knm]]
v13	Kiln inlet temperature #1 [700 - 1600 [°c]]
v14	secondary air temp [0 - 1370 [°c]]
v15	Kiln main drive speed control [0-100 %]
v16	Kiln main drive current [0 - 217 [a]]
v17	Kiln main drive torque [0 - 150 [knm]]
v18	Kiln inlet temperature #1 [700 - 1600 [°c]]
v19	Secondary air temp [0 - 1370 [°c]]
v20	Tertiary air to preheater temp [0 - 1200 [°c]]

Examine quantitative survey data to find notable patterns, trends, or linkages between the variables as shown in Figure 48. The KILN MAIN DRIVE SPEED CONTROL [0-100 %] as the variable which has the highest correlation R^2 with the CO_2. The typical speed of the main drive for the kiln is approximately 4.50 revolutions per minute (RPM). This means that the kiln speed has influence on the calcination degree and can be used as a predictor of the amount of calcination degree through the cement manufacturing process.

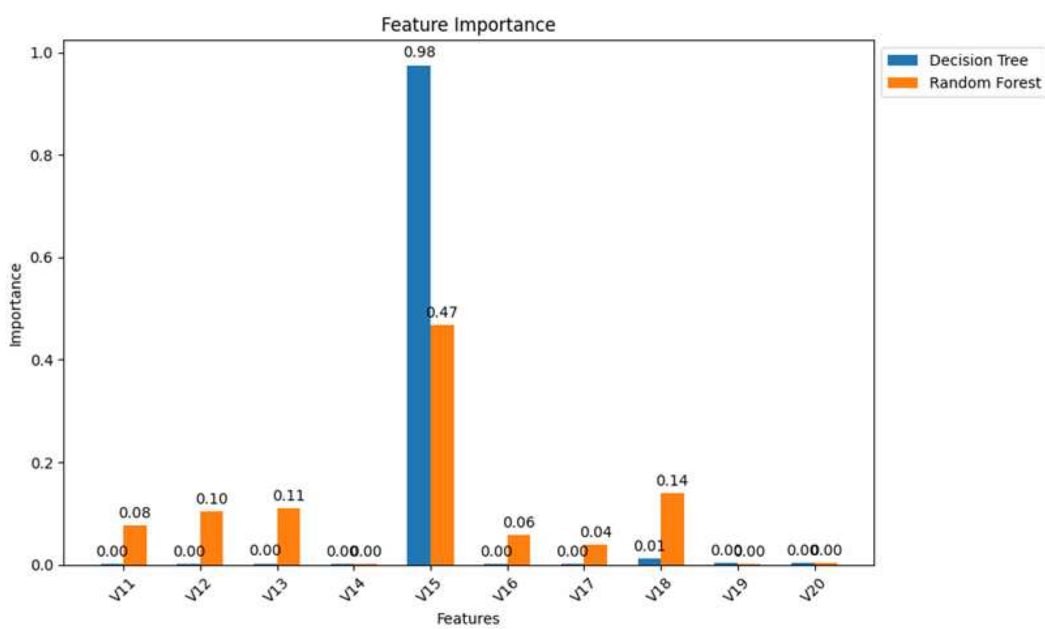


Figure 48 shows the most correlated variable with CO_2

The dataset was used to train 5 different regression model types. The model that yielded the lowest Root Mean Square Error (RMSE) within each category was selected to predict the output variables of apparent calcination degree and CO_2 molar fraction. Figure 49 below shows the predictive modeling of the dataset using multiple regression analysis

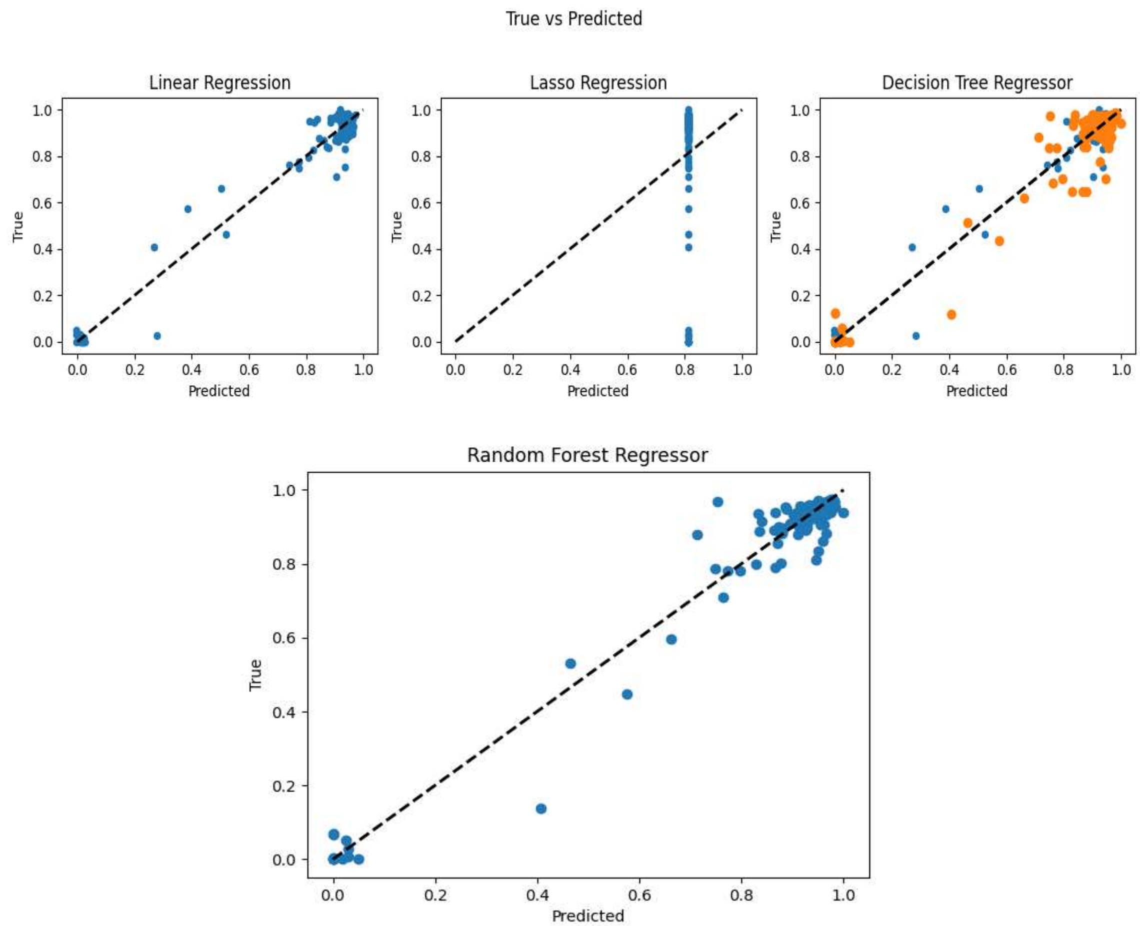


Figure 49 shows the various predictive models

The RMSE for the linear, ridge, decision, and random regression are all equal to or below 0.05. The Lasso regression analysis is 0.24. Predictions made by a model with a lower error are more accurate. RMSE values are expressed in the same units as the dependent (outcome) variable and range from zero to positive infinity. Figure 50 shows the RMSE with different algorithms for the predictive modeling.

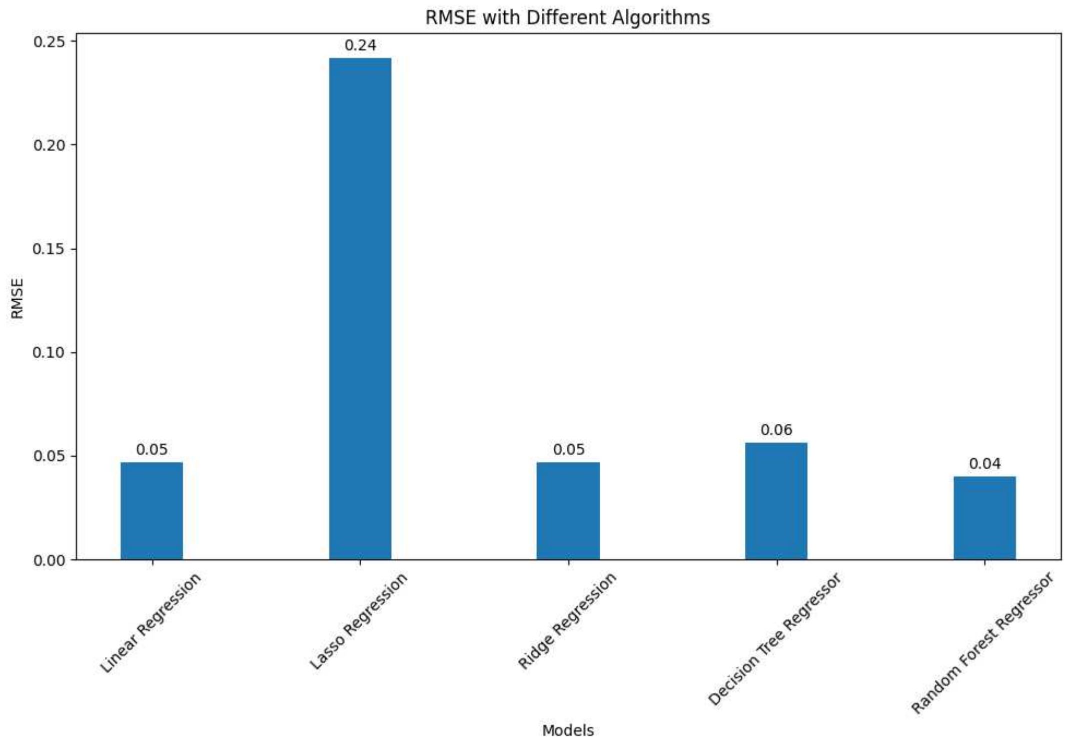


Figure 50 The Normalized RMSE with different Algorithms for the predictive modeling

4.2.3 Preheat Tower and Kiln Systems

The combined system which included the preheat tower and the Kiln data set was considered. Results for the Python analysis are reported herein. Table 16 shows the statistical analysis of the dataset analysis of the correlation coefficient between the two highest systems.

Table 16 Correlation coefficient comparisons between the two highest correlated system values from the preheat and kiln

Correlation	**Value**
Preheat.stg.3 cyclone 3a gas outlet pressure	0.940095
Kiln main drive speed control	0.985176

Initially, feature correlation heat maps were employed to narrow the focus of our research by identifying potential correlations and excluding variables with minimal relevance to CO_2 generation. The data sets run showed the highest correlations among the cement manufacturing process. Heat map of the local sensitivity analysis results for the final model using manufacturing real-time instrumentation process historic data of the kiln entire system as input variables against output data of CO_2 (Figure 51). After narrowing down the results from both the preheat tower and the Kiln systems, a Pearson correlation analysis was conducted to assess the linear relationships between each measurement and the corresponding CO_2 levels calculated over the same time frames.

$$r = \frac{\sum(x_i - x_{average})(y_i - y_{average})}{\sqrt{\sum(x_i - x_{average})^2 * \sum(y_i - y_{average})^2}}$$

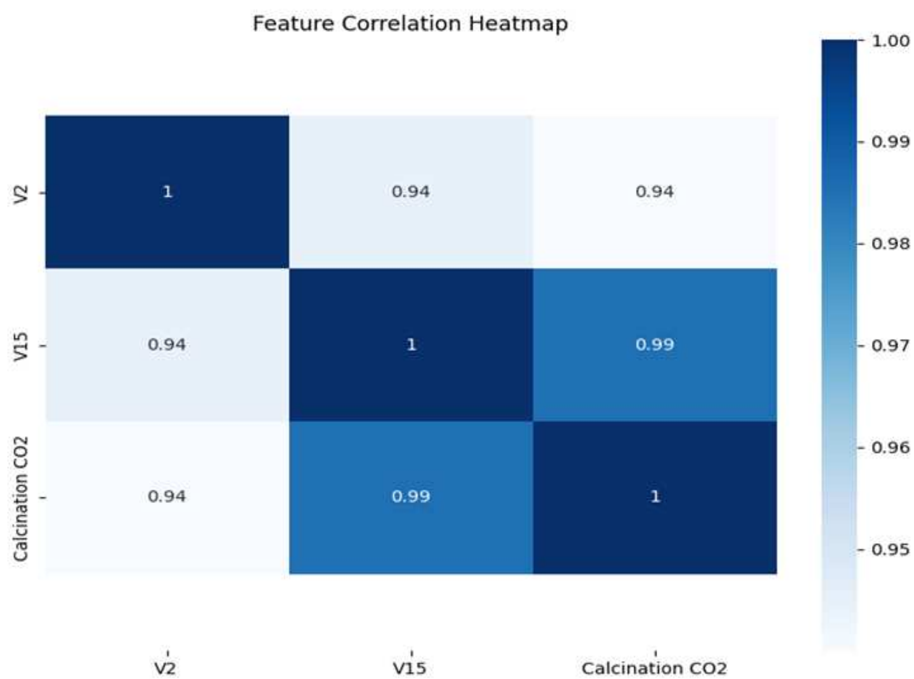


Figure 51 shows the heat map of the Preheat and Kiln Process data sensitivity analysis

The highest yielding outputs from both the previous Kiln and Pre-heat analyses were then compared to produce the highest overall correlation of the dimensionality-reduced set of features using multivariate regression. Figure 48 shows the KILN MAIN DRIVE SPEED CONTROL as the variable which has the highest correlation R^2 with the CO_2. The pressure daft at stage 5 is -19 mBar and stage 1 are draft -81 mBar. Taking into account all the system data, the correlation analysis indicates that the draft pressure in stage 1 of the preheat tower is the most influential factor in predicting the calcination process and CO_2 emissions.

Figure 52 shows features of importance of the dataset using multiple regression analysis. V2 and V15 can be referenced to Table 4 and 6.

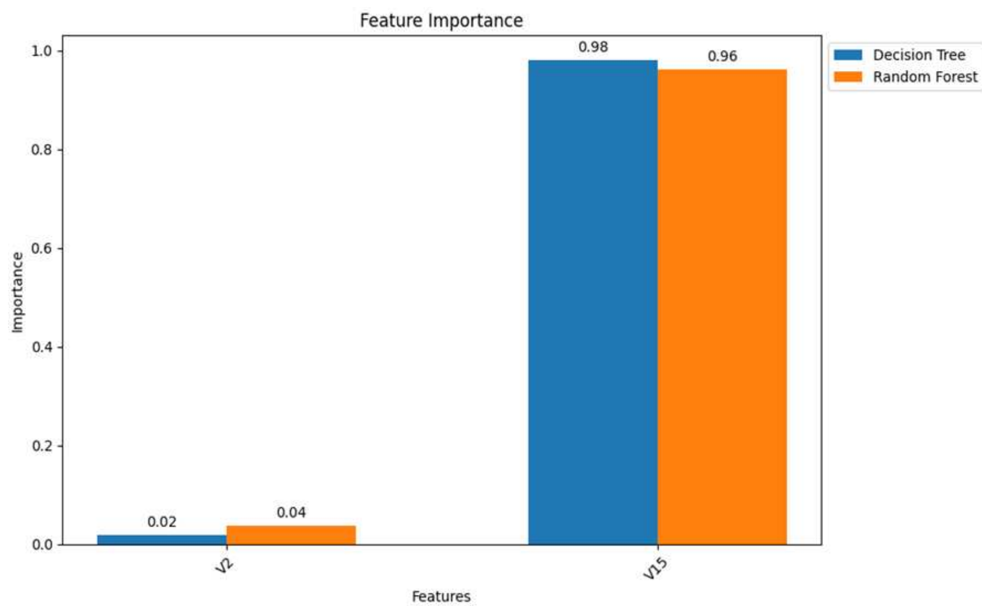


Figure 52 show the heat map of the Preheat and Kiln Process data sensitivity analysis

4.3 Summary of Results

The results presented herein are the output of the research methods presented in Chapter 3. The results clearly show that the method adopted for this research can be used by the cement industry to help optimize raw material usage at the quarry reduce the footprint of the quarry due to optimized modeling of geological deposit, reduce the mining of overburden waste due to precise development of quarry, and reduce the footprint of overburden waste dumps because of optimized use of overburden material in the limestone mix requirement of the clinker manufacturing. The results also demonstrate that CO_2 can be predicted using cement manufacturing conditioning monitoring data collected in real-time by sensors installed throughout the preheat tower, calciner, and kiln in addition by employing machine learning capabilities. Even though quarry operation and calcination processes metrics have many influencing factors, and many cannot be adequately captured in existing metrics, the results show linear relationship with less scatter plots. This means that mathematical models will be complete or accurate in using to predict cement manufacturing data.

Chapter 5 – Discussion of Research Study

The rapid expansion and interconnection of the world's economy and the necessity for infrastructure development due to population growth are two underlying factors driving the increased demand for cement on a worldwide scale. The sector greatly raises living standards worldwide and helps related industries by directly producing jobs and providing other advantages. Cement has had many ameliorative effects on society and politics throughout the years, but its manufacture has also had pejorative effects on the environment and politics. The problem statements were defined in Chapter 1 throughout the research project. Chapter 2 illustrated how other researchers have looked at these issues related to cement manufacture as well as describing what literature is available on these specifically defined problem statements. The unique research approach used to address the issues listed in Chapter 1 is disclosed in Chapter 3. The results of the investigation are succinctly and impartially presented in Chapter 4. In Chapter 5, the results of Chapter 4 are summarized and placed within the larger framework of the study.

5.1 Raw Material Optimization and Wasting

Quarry operation plays a significant role in cement manufacturing. The quarry is the main source of raw material for cement manufacturing. Even though the quarry plays such a significant role in cement manufacturing, little attention is dedicated to its operation to understand its impact on the environment and its impact on the quality of clinker quality based on kiln feed. In addition, cement manufacturing has not adopted innovative technologies and digitization in the quarry to improve operations. This section discusses the results presented in Chapter 4 after using existing technology and data management-controlled feedback loops to improve quarry operation. Also, by using data management control feedback loops to control mix design at the raw mill, a significant improvement is made to the quality.

5.1.1 Reduction in limestone usage in the manufacturing of clinker

As mentioned in previous chapters, limestone is the core raw material for cement manufacturing. Limestone quarrying affects natural resources and groundwater. To reduce the impact, most nations have strict regulations and permit requirements before establishing a quarry. The reduction in limestone usage in the manufacturing of cement has a huge impact on the problems identified in the chapter of this study. Therefore, efficient quarry management is an important component of the cement manufacturing process and can reduce costs and reduce the impact on the environment. The objective of long-term production planning for limestone mines is to ensure the cement plant receives a well-balanced combination of raw materials. Figure 53 indicates the execution of a research method model described in Chapter 3 regarding mine planning and the outcome within 5 years of operation of the quarry. It illustrates how well-formed the benches are, adding to safety, and how the output of limestone approaches the study mine's target production's maximum permissible limit. This helps limit the impact of the destruction of green fields and the ecosystem. Also, it allows for better management of groundwater with less impact on surface water.

Figure 53 shows the well-established Union Bridge Quarry with benches and multiple levels. It also shows less area impact which is positive for the environment. This was possible because of the research method adopted and implemented (Picture taken on-site August 2023)

Figure 53 indicates the execution of a research method model described in Chapter 3 regarding mine planning and the outcome. This as mentioned required long and short-term planning. Presented herein is the discussion on how this was executed in the field. The limestone production scheduling for an open pit mine can be described as determining the order in which 'blocks' should be extracted to achieve a specific goal while considering a range of physical and resource restrictions. The success of a cement plant's operation hinges on the availability of high-quality raw materials in adequate quantities. The quality of limestone extracted at any given time shapes the raw mix for the cement plant. Consequently, the objective for the owner of the cement production is to maintain the levels of undesired oxides below a specified threshold while meeting the quality requirements for the desired oxides. If limestone is taken directly from one area of the mine, there's no guarantee that the quality standards will be fulfilled, even though the mine can offer a set amount of limestone. To satisfy the cement plant's quality requirements, limestone from different areas of the mine or outside sources is frequently mixed. To ensure that the cement plant receives raw materials of the right quality and quantity, proper mining planning is essential. When planning a limestone, mine, several elements must be considered, including geotechnical, economic, and geological concerns. Limestone mine planning can be categorized into two classes: long-range and short-range mine plans. Long-term mine planning is usually finished during the building of the cement plant. In the event of unanticipated circumstances, such as modifications to output, the requirement to provide raw materials from other mines, changes to leases, adjustments to management, etc., long-term mine planning is evaluated. On the other hand, short-range planning takes operational control and daily optimization into account. The amount of limestone that the mine's final pit will supply to the plant must be estimated over a long period. The ultimate pit limit that maximizes profit while limiting footprint, using less limestone in the mix and less overloaded material in the mix, has been determined by studies utilizing the modified mining model on automated open-pit design described in Chapter 3. Table 17 shows the impact on limestone and clinker production results between 2019 and 2020. Data shows an increment of 2% in limestone for cement but an increase in clinker production by 4%. This is due to better reactivity during manufacturing and an increase in overburden waste in optimized raw material from the quarry. The performance of the kiln is affected by variations in the quality of raw materials. The standard deviation of kiln feed LSF experienced a 45 percent improvement, leading to a 65 percent reduction in the variability of kiln feed. The reliability of the kiln was 98% in 2020 compared to the previous year of 96% in 2019. This is also reflected in clinker tons per operating day (TPD) which increased from 6,883 to 7,061 an increment of 3% of production per day. This can also be broken down as the clinker tons per operating hours (TPH) increased from 294 in 2020 to 287 in 20219.

Table 17 shows the Heidelberg Materials US Union Bridge Plant Production Data

Year	Limestone (tons)	Clinker as a percent of Limestone (%)	Incremental of limestone comparing 2020 to 2019 (%)	Clinker (tons)	Difference between 2020 and 2019 Clinker Production (tons)	Incremental of Clinker comparing 2020 to 2019 (%)
2019	3,123,970	71%	2%	2,222,921	92,732	4%
2020	3,179,904	73%		2,315,653		

The objective of this model is to maximize profit while considering several other factors, including calculating the eventual pit limit and the life of the limestone mine. This model did not use any additional limestone from outside sources to meet the needs of cement manufacturing. The incremental clinker from 2019 to 2020 due to the implementation of the adopted research method increases by about $4.6 million. It was discovered that the branch and cut strategy can produce feasible limestone solutions for over 75 years of life. The 75 years of quarry life was possible because of the blending of dolomite, limestone, and overburden which increased the volume. Also, is crucial to remember that the techniques used to optimize the limestone blend with the addition of overburden waste in the mix and construct the quarry pit did not compromise the quality of the limestone used to make cement (Table 18). The statistical analysis that was done indicates that the clinker and raw meal material produced all fulfilled the required quality standard. Table 18 provides the quality data expected by ASTM standards for cement manufacturing. This quality data is also important for customers since concrete curing is very dependent on this quality data. Table 18 shows that the strength of cement even increased by 0.8% for 24 days.

Table 18 shows that the quality of clinker and cement was not impacted by the changes made due to the raw material optimization.

Quality Indicators Clinker			
	2019	2020	Target
Alite Sum	58.99	59.81	> 60
Belite	17.28	15.16	10 to 20
C3A	8.03	8.00	< 8.0
Freelime	0.93	0.96	< 2.0
LSF	96.02	96.33	96.5
NaEq	0.5	0.5	< 0.60
SR	2.38	2.39	2.2 to 2.5
AR	1.49	1.5	1.4 to 1.8

Quality Indicators of Cement			
	2019	2020	Target
1 day	15.48	15.84	16
28 days	41.76	42.11	41.4
Alpine	6.42	6.74	7.00
Blaine	381	377	380
325um	3.49	3.36	4.00
SO3	2.91	2.96	2.95
Vicat	158	154	140

It is important to note that generating more profit with less material extraction is possible when using economic parameters as the target function in production planning. Furthermore, the study's selected methodology can be applied by other cement production enterprises to lessen the amount of limestone utilized and the environmental impact of quarries, both of which benefit groundwater bodies and the environment. Reduced limestone resources needed to produce the same amount of cement are essential for the cement industry, which is currently being criticized for its role in the destruction of the environment worldwide.

5.1.2 Reduction in sand usage in raw materials

One of the most vital minerals in the modern world is sand. It is the world's most exploited solid material and the second greatest natural resource by volume, behind water. The current global need is 50 billion tons annually or 18 kg per person per day on average. Historically, sand has been mined from natural resources such as rivers and coasts. However, due to the severe environmental effects, including erosion in rivers and beaches and changes in the pH levels of the water, new laws have been put in place to preserve these sources. As was noted in Chapter 2, sand is an essential component of the mixture used to make cement. It contributes to the clinker formation's silicate portion. Sand is often imported by outsourced to the cement plant, where it is used as a raw ingredient in the raw mill. In many developed nations, the scarcity of sand has given rise to sand mafias. Sand thieves are referred to as a "sand mafia." Due to increased demand and dwindling supply, sand theft is an issue. Although it is frequently prohibited, sand mining is regulated in many areas. India's biggest organized crime group is involved in illegal sand mining. Therefore, optimizing raw materials to reduce the use of sand in cement manufacturing is key. The research adopted and the results obtained indicate that some of the sand was displaced from the mix because of the use of the overburdened waste material in the mix which had some silicate. This resulted in 150,000 metric tons of overburden used in the raw material mix in 2020 as compared to 2019. This increase is significant since it helps reduce sand by 4% usage (Table 19) which saves the company millions of dollars in outsourcing and helps with the illegal mining of sand.

Table 19 shows the impact of overburden waste used in the mix on sand usage

Year	Limestone	Sand (tons)	Sand as a percent of Clinker (%)	Decremental of limestone in 2020 compared to 2019 (%) per clinker difference	Difference between 2020 and 2019 Sand used	Clinker (tons)
2019	3,123,970	226,046	10.17%	4%	(3,514)	2,222,921
2020	3,179,904	222,532	9.61%			2,315,653

This is all possible because of use of quarry modeling software tools are used for planning and the adoption of a data management architecture control loop feedback system.

5.1.3 Reduction in Overburden wasting and management of waste dumps

The research study shows a significant reduction in quarry overburden wasting when quarry modeling software tools are used for planning, and the adoption of a data management architecture control loop feedback system. Overburden waste management in quarry operations is one of the most difficult aspects of mining. Waste dumps can have tremendous negative effects on the ecosystem, as mentioned in Chapter 2. The trash is worthless to the industry and is often limited to the area around a mine rental location, with sporadic concentrations occurring on public land. The size of the mine affects how much garbage is produced. As a result, less overburden debris was removed to reveal limestone by designing the quarry and optimizing the footprint utilizing the research methodology in the study. Opencast mines are therefore more pollution intensive than underground mines since they generate a lot more rubbish. Mining waste damages life in addition to polluting the environment. Because of the quarry's life cycle, we must lessen the waste footprint's impact and offer reclamation techniques to address it. This raw material optimization allows a reduction in overburden wasting and waste dump footprint which has less impact on surface water, ecosystem, and groundwater. Table 20 shows the improvement of the addition of overburden waste to the quarry mix from 2019 to 2020 of increase of 130,000 tons. This is signification looking at the bigger picture which the life of the quarry is 75 years. A total of 11,250,000 tons of waste will be used in the mix avoiding large areas of land (38 acre) for storage.

Table 20 shows the overburden used in the raw material optimization mix

Year	Limestone	Overburden Waste in Mix (tons)	Overburden as a percent of Clinker (%)	Difference between 2020 and 2019 Overburden in Mix (tons)	Clinker (tons)
2019	3,123,970	20,000	1.12%	130,000	2,222,921
2020	3,179,904	150,000	6.48%		2,315,653

The application of life cycle planning for the waste generated at Heidelberg Material US's Union Bridge Cement Plant Quarry, the case study location, is depicted in Figure 54. The well-reclaimed benches with sediment control and sowing ponds are depicted in Figure 54. The social obligations of a well-designed and organized operation where research is undertaken and has a significant impact on society are demonstrated by this design and by associated well-maintained reclamation and mining programs. In addition, the waste dump is being tested for possible use as SCM material in concrete which will displace the cement used in concrete therefore reducing CO_2 emission. If this works, it provides the life cycle of the quarry operation to full use where the waste is 100% consumed.

Figure 54 shows a responsible life cycle-designed overburdened waste design dump at Heidelberg Materials Union Bridge Quarry. Note that this an active waste dump which is been concurrently reclaimed as mining occurs ((Picture taken on-site August 2023)

5.2 CO_2 Prediction

The threat posed by climate change is one of the biggest environmental issues that our civilization is now dealing with. Carbon dioxide is one of the primary greenhouse gases (CO_2). The current study aims to determine which factors, taken together, have a larger overall influence on CO_2 emissions during the cement production process. Clinker reactions and calcination are the two main chemical processes in a Portland cement manufacturing facility. These reactions typically occur in the rotary kiln and cement calciner, respectively. As a byproduct of calcination, the phase in the cement manufacturing process that uses the greatest energy, CO_2 is produced. As was already indicated, the reactions of the limestone and the use of fossil fuels for thermal energy are the sources of CO_2 emissions. Herein explains the analytical output from the predictive CO_2 results obtained in Chapter 4.

5.2.1 Impact of Research Study on CO_2 Emission in the Cement Industry

As stated in the study, approximately 8% of global carbon dioxide emissions, are caused by the cement sector. To help the global cement industry, one must follow the roadmap and reduce the CO_2 emissions footprint of cement production. The cement industry is now exploring a wide range of approaches. According to a 2018 assessment by the International Energy Agency, the cement manufacturing sector is implementing several measures to contribute to NetZero CO_2 emissions by 2050. How does this research work of using machine learning to predict CO_2 fit into the broader concept of reaching the goal of NetZero 2050? For years the cement industry has struggled to understand how process monitoring variables affect the calcination process. This is because of the complexity of data generated by the multiple sensors to measure process asset performance variables and process variables of the preheat tower and kiln system. Because of this complexity, the cement industry has mostly relied on the IPC empirical formula to calculate CO_2 emission which is based on the volume of limestone used for clinker production and the volume of fossil fuel used for thermal heat as mentioned in Chapter 2. The accuracy of these calculations is sometimes questioned. In addition, because of a lack of understanding of how measured process asset performance and process variables affect CO_2 emission, nothing is done to optimize assets and processes to influence CO_2 emission during the calcination process which contributes to about 60 – 70% of CO_2 emission in the cement plant. This research work was performed to demonstrate that machine learning can be used to understand the impact of the assets and process variables on CO_2 emission during cement manufacturing even with the complexity of the processing. Sensitivity analysis data presented in Chapter 4 shows correlated variables with CO_2 and indicates that the cement industry should start adopting these powerful tools to better optimize their operations. The study also shows that these variables can be manipulated to achieve optimal calcination to help reduce excessive thermal heat application and limestone reaction and therefore reduce CO_2 emission. It is important to note that quantifying the exact quality of reduction in CO2 emissions requires a controlled environment simulation model (CFD) and then in a lab before implementing them in the manufacturing process. This contributes to the pathway of reducing CO_2 emissions in cement manufacturing through operational efficiency and excellence which has need noted by the IEA as one of the pathways to achieving the NetZero goal in 2050. Why are we so confident that the process of optimizing the most correlated variables can reduce CO_2? This is because Feldmann [279] reported that one plant's application of AI in its autonomous mode of a raw mill resulted in throughput and energy efficiency improvement rates of up to 10 percent. As a result, profits increased from additional revenues and reduced energy, as well as reduced CO_2 emissions. This work needs to be verified in future research work in order to further support the conclusion made by Feldmann [279]. Figure 55 shows the improved productivity steps from AI asset optimization reduce operations by 500 hours per year and increase production by more than 10 percent. Therefore, there is existing proof that by optimizing two variables which has a strong correlation with CO2, emissions can be reduced.

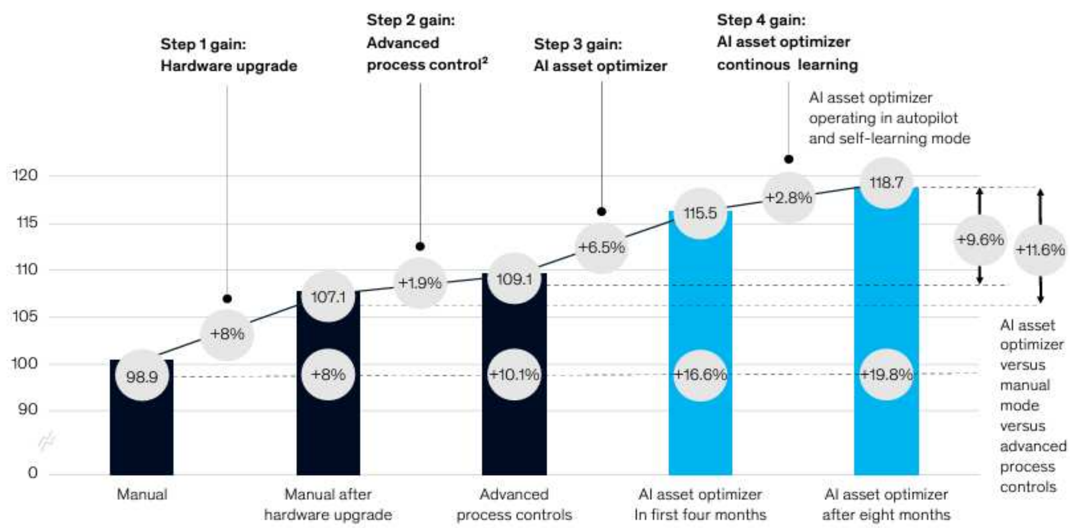


Figure 55 shows how AI was used to optimize of the raw mill which reduces energy usage and reduces CO_2 emission by 10% [279]

In addition, the study demonstrated that CO_2 can be predicted where the predicted is well corrected with the truth. The prediction of CO_2 using machine learning can help cement plant operators better appreciate and quickly get data on how much CO_2 is been emitted in real-time. This will influence their decision-making and make way for mitigation plans which can significantly affect CO2 emission. An example is that they can introduce alternative fuels to help reduce CO emissions rather than their overreliance on fossil fuels. The next step is to develop software that cements manufacturing plants can tie to their process and asset performance variables database prediction will be in real-time. As mentioned in Chapter 4 two factors are crucial to the pyrosystem of the manufacturing process, as the study's results using machine learning. The inquiry considered industrial data from the past. The first of the two variables is PRE-HEAT.STG.3 CYCLONE GAS OUTLET TEMP. [0 - 900 [°C]]. (2) MANUAL KILN DRIVE SPEED CONTROL. Here, these two aspects are examined in detail. Herein discussed in detail why these two variables play a key role in CO_2 emission in the pyrosytem and how optimizing the two variables can reduce CO_2 emission during the calcination process.

5.2.2 Preheat.STG.3 Cyclone Gas Outlet Temp. [0-900^{o}C]

As was previously mentioned, the calcination of the limestone blend starts during the preheater cyclone phases. The preheat temperature's rationale concerning the correlation is supported in this section. Temperature has a big impact on CO_2 emissions in a lot of situations. Higher temperatures and more thorough burning of fossil fuels could result in increased CO_2 emissions. Higher temperatures allow these processes to proceed more quickly, which increases emissions. When the temperature rises above 925 °C, limestone begins to break down rapidly. At standard pressure, limestone breaks down at 898 °C. The process doesn't begin until the temperature climbs above the temperature at which limestone's carbonates dissociate, which is typically between 780 and 1340 degrees Celsius. Temperature causes an increase in agglomeration and shrinkage. The temperature needs to be maintained above the dissociation point and the CO_2 that is evolved throughout the process needs to be removed. The desired CaO layer is left behind when the $CaCO_3$ finally dissociates from the particle's outer surface inward. Because of this, the process depends on a fire that is hot enough at least 800 degrees Celsius to allow for decomposition and a long enough residence period that is, keeping the limestone or lime at 1,000 to 1,200 degrees Celsius for a reasonable period to control its reactivity. The crystalline structure of the limestone, its internal strength, and the size of the crystals that form after calcination are the factors that influence calcination. During the calcination process, smaller crystals combine to create larger crystals, which causes the larger crystals to compress and lose volume.

Higher temperatures during calcination lead to greater agglomeration and shrinkage. Furthermore, there is a relationship between limestone's density and crystal structure. The crystal shape, which also influences the density of the limestone, determines the vacuum area between crystals. Because greater gaps facilitate the passage of CO_2 gases, volume is decreased during the calcination process. Some limestones, because of their crystalline structure, disintegrate during the calcination process. This type of limestone is not appropriate for calcining. The action of another limestone is the opposite. This type of limestone is calcined until it becomes nonporous and so dense that CO_2 cannot escape. The reactivity of the material is used to measure how fast lime reacts to water. Ground lime is slaked in water as part of a test procedure to see how reactive it is. Lime's reactivity is affected by a variety of processes and raw material-related factors. These variables include (i) the temperature and length of the burning process, (ii) the limestone's crystal structure, (iii) impurities, and (iv) the fuel type and kiln. Lime is usually classified into four types based on its level of reactivity: (i) dead burned, (ii) hard, (iii) medium, and (iv) soft. It is common to describe lime as dead burned, hard, or medium burned. The characteristics of lime are also influenced by the limestone that is utilized as feedstock and fuel. For example, gas-fired parallel flow regenerative kilns usually create high-reactivity lime, whereas coke-fired shaft kilns often produce lime with medium to low reactivity. The chemistry and reactivity of lime are the main aspects that affect its use. In the Union Bridge Plant, coal is used as a thermal fuel source to raise the temperature in the preheat tower. Additionally, the coal contains carbonate compounds that, when burned, release carbon dioxide (CO_2) and raise the temperature in the preheat tower. It is always possible that optimal heat temperature is not considered for the calcination process through the calciner on stage 5 and the cyclones in the preheat tower. Excessive heat means more burn and that is correlated to CO_2 emission. To provide heat, part of the grinded powdered coal start burning at the calciner then by negative pressure the heat temp is sucked through negative pressure airflow throughout preheat tower cyclones on different stages. The hot air encounters the raw meal material and flows down the preheat tower calcination starts in the preheat tower and CO_2 emission also starts. To achieve a certain calcination degree excessive heat is sometimes used which can be avoided. Table 21 shows the consumed coal for the 2020 and 2019 cement manufacturing at the Union Bridge Plant.

Table 21 shows the volume of coal used in 2020 and 2019. The mmBTU of the coal used is in the table

Year	Limestone	Coal (tons)	Coal as a percent of Clinker (%)	Annual Average (mmBTU)	Clinker (tons)	Clinker Tons per operating hour (TPH	Average Yearly Clinker (tons/day)
2019	3,123,970	274,096	12.33%	9.98	2,222,921	287	6,883
2020	3,179,904	287,390	12.41%	10.21	2,315,653	294	7,061

Deterioration of dolomite and dolomitic limestone is far more challenging. Decomposition may involve one, two, or even more distinct stages in addition to transitional ones. The following phases' reactions are involved: $CaCO_3.MgCO_3$ + heat = $CaCO_3.MgO + CO_2$, $CaCO_3.MgO$ + heat = $CaO.MgO + CO_2$, and $CaCO_3.MgCO_3$ + heat = $CaO.MgO + 2CO_2$. The decomposition of dolomite and dolomitic limestone requires temperatures ranging from 500 to 750 degrees Celsius. Depending on the temperature, technologies like carbon capture and storage that reduce CO_2 emissions from industrial operations can work better or worse. All things considered, rising temperatures can exacerbate the problem of CO_2 emissions and fuel global warming, which has a range of consequences for the environment and civilization. The degree of calcination that results in the amount of CO_2 emission is closely associated with the temperature in the preheat tower, as this explanation and the findings demonstrate. There exists a correlation between the total heat use and the temperature. This unequivocally validates the outcomes of predictive analytics and sensitivity analysis carried out with machine learning technologies. This explains why temperature in stage 3 and CO_2 emission correlate as seen in the results section.

Approximately 85–90% of the fuel used by the world's cement industry comes from coal. It serves as a source of energy for the calcination process heating in the calciner and kilns, which are often burned in a ground-up manner. To make one ton of cement, 0.24–0.50 tons of coal is needed. Therefore, the efficiency of coal usage in cement manufacturing based on the optimization of the asset and process variables reduces CO_2 emissions but the percent reduction must be proven by simulation modeling (CFD) and lab experiments. Based on Feldmann [279] findings such optimization can reduce CO_2 by 10%.

5.2.3 Kiln Main Drive Speed Control

The statistical research shows that the kiln main drive speed control variable has the highest correlation with CO_2. The primary drive speed of a kiln, which is often connected to the shell or drum's rotational speed, can directly affect CO_2 emissions. The connection is complex and dependent on various factors and procedures. Why is the calcination process being affected so much by the kiln's main speed control? The influence is explained by the following summary arguments. The drive consists of an electric motor with an auxiliary drive, a gearbox, couplings, and a frequency converter. Auxiliary drives can be employed with diesel engines. A rotary kiln is used to continuously raise materials' temperature to a high point (calcination). It rotates normally at a speed of 1 to 3 rpm, but it can occasionally reach 5 rpm. The length of time materials stay within the kiln is determined by the main drive speed and determines how much calcination and reaction occurs. Higher main drive speeds may cause shorter residence times, which could affect the quality of clinker and the efficiency of fuel used in the kiln. The primary driving speed has an impact on CO_2 emissions and energy consumption. The primary drive speed has an impact on the efficiency of calcination, which in turn affects the energy consumption and emissions generated by these processes. The main drive speed may affect the firing process, which may affect energy consumption and emissions. However, the relationship is not linear, as other factors like fuel type, feed material composition, kiln design, and process optimization also play significant roles. Modern kilns with advanced emission- and energy-reduction technologies can decrease the impact of main drive speed on CO_2 emissions. To achieve the desired provision of stable kiln operation, the calcining zone and the maximum temperature in the traveling bed need to be positioned such that the coal has a suitably lengthy travel time as it completes calcination. With the least amount of feed and, ideally, no extra fuel, effective calcination can be achieved (burning volatiles provides at least 75%, if not more, of the heat required anyway). Undoubtedly, one of the most important process variables is the maximum temperature, which is selected or changed depending on the coal's characteristics. The calcining zone and the position of maximum temperature move toward the discharge end when the kiln's rotation speed increases; on the other hand, when it slows, the opposite happens.

As explained herein, we can see why the kiln main drive speed control had the highest correlation with CO_2 emission because of its impact on the calcination process. The kiln-burning zone is the area where more coal is used as a thermal source of heat and, therefore the most emission of CO_2. The zone also accounts for the maximum calcination reaction for the CO_2 emission of limestone. There's a clear impact of time surface reaction within the zone and the speed of the kiln drives its effects. This research study does not quantify the percent possible reduction in CO_2 if the kiln main drive speed control is optimized as indicated by Feldmann [279] in the case of using AI for raw mill optimization. To quantify the CO_2 emission reduction will require a second phase research study as a continuation of this work presented herein where simulation models can be conducted with controlled boundaries (CFD) and then a lab experiment before implementation in the field. Based on Feldman [279] findings such optimization can reduce CO_2 by 10%.

5.2.4 Impact on Carbon Reduction and Storage in the Cement Final Usage

As discussed in Chapter 1, concrete has been utilized for shelter for over 6,000 years. However, it's noteworthy that half of the concrete ever produced is less than 20 years old. The transformation of cement into concrete involves the addition of water, sand, and stones. The water triggers reactions that solidify the material and bind the aggregates. Currently, the global concrete industry has an annual value of approximately $1 trillion. Consequently, any new eco-friendly cement or concrete technology has the potential to exert a substantial influence on global emissions. The cement and concrete industry have long sought eco-friendly solutions. As mentioned, employing modern tools like machine learning and AI will help improve operational efficiency and help reduce CO_2. But the concrete side of the industry which is the end use of the cement product is also looking for innovative tools to improve CO_2 emission. For example, it recycles a great deal of industrial waste. It has already used 26 million tons of industrial byproducts otherwise destined for landfills. Concrete's role in CCUS has been further expanded for a more sustainable future. Adding CO_2 can make the concrete stronger. If CO_2 comprises just 1.3% of the weight of concrete, the material's hardness can increase by around 10%. That reduces the amount of cement needed in a structure along with net emissions by about 5%. Optimizing carbon capture in concrete is an active area of research which is been exploded. Cement and concrete both absorb CO_2 from the air by converting calcium-based components back into limestone. The potential there is huge: in theory, roughly half of the process CO_2 emissions from cement manufacturing could be reabsorbed. Monkman et al., (2016) show that the CO2-injected concrete batch's compressive strength measurements showed a 14% improvement for the cylinders tested on day one and a 10% improvement on day three. At ages longer than 7 days, when the benefit fluctuated between 1 and 8%, it was functionally equivalent to the reference. At one and three days, the concrete that had received the CO_2 dose turned out to be stronger than the concrete made with the traditional accelerator. Between the two batches, there was no variation after that until the latter demonstrated a 14% benefit at 91 days and an 8% benefit at 182 days. Figure 53 shows the compressive strengths of different samples compared to the injected CO_2 concrete. This is very promising for the reduction of the CO_2 pathway. By using machine learning as shown in the study presented in Chapter 4, cement manufacturing companies play a key role in advancing the technology of capturing CO_2 at the plant level and injecting it into concrete as a storage means. This can all be considered as part of the broader picture of reaching the goal of NetZero by 2050.

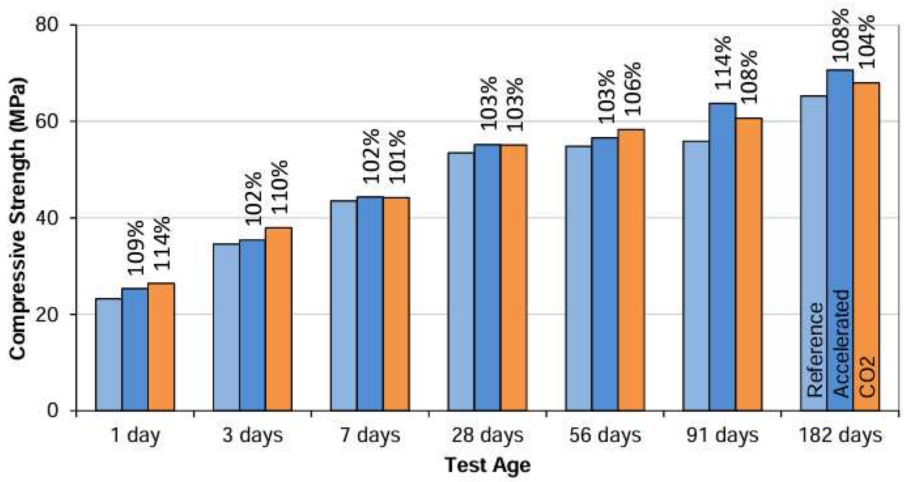


Figure 56 shows the compressive strength results of samples (Monkman et al., [280])

5.2.5 Summary of CO_2 Emission study

Cement manufacturers must adopt the research method presented here regarding how to predict CO_2 emissions during clinker production for several reasons. The strategy now used by the cement production industry covered in Chapters 3 and 4 is less time-consuming when using operational process monitoring data to estimate CO_2 with machine learning for cement manufacturing. As described in Chapter 2, this method uses empirical calculations and numerous scale calibrations based on the scale volume of limestone and fossil fuel consumed to make one ton of clinker. Errors are easily introduced using this procedure, and attempts to limit the error necessitate multiple audits, which negatively impacts the manpower of the cement factories. In addition to saving money, the machine learning prediction method improves knowledge of the critical process variables that directly affect CO_2 emissions.

There are still notable deviations of up to 50% from the average or higher in throughput, energy consumption, and other operational parameter performance volatility for manufacturing cement. The main reason these kinds of events continue is that standard automation and control systems are ill-suited to manage activities involving chemical processes, which are inherently unstable. Machine learning algorithms can detect deviations from conventional values by examining sensor data. Cement producers can modify their production procedures thanks to this real-time analysis, guaranteeing a constant level of product quality. Decisions about factors that can be improved to reduce CO_2 during the manufacturing process can be made rapidly by incorporating real-time anticipated CO_2 emissions from cement production. It is noteworthy that the existing methodology relies on monthly production volume data for computation. That is a delay in outcomes that prolongs the time for any significant decision that could have been made right away.

Cement production plants may make data-driven decisions and have access to real-time effect information due to machine learning predictions. As previously mentioned, artificial intelligence (AI) and machine learning are here to stay and have been applied to show that the calcination complex process can be evaluated to see which variables have the most influence on CO2 emission. Even though the study does not include quantification of possible reduction if the variables are optimized, we believe that there is a possible 10% reduction in CO_2 but this must be studied. This research study manages more complex process data when compared to the IPCC technique, which is only based on tonnage of clinker produced and tonnage of fossil fuel used. This modeling allows for consideration of nonlinear process and variation in variable inputs. Furthermore, the model performs better in modeling the process functions of the cement production systems and explaining the origin of the CO_2 reduction variable in the cement manufacturing process. In addition, the study has demonstrated that CO_2 The current net zero objective established for 2050, which involves adopting operational efficiency, requires cement makers to accept and use machine learning CO_2 prediction.

The cement industry is under a lot of pressure to improve its CO_2 emission and environmental impact due to the manufacturing of cement. To combat climate change, many nations have set rules and goals for reducing emissions. If cement producers don't achieve these requirements, they risk fines or production restrictions. Using eco-friendly methods can improve a company's reputation and brand image since they are consistent with corporate principles and show a commitment to sustainable development. By reducing energy consumption and waste, the use of energy-efficient technologies and alternative fuels lowers operating costs while also reducing CO_2 emissions. Businesses may have a competitive advantage in the market by appealing to environmentally concerned investors and customers by proactively addressing environmental issues and developing sustainable solutions.

Overall, reducing CO_2 emissions during clinker production plays a significant role in the overall goal of the cement industry and the long-term viable path to the success of cement manufacturing operations. Here, total anthropogenic carbon dioxide (CO_2) emissions worldwide are brought almost completely down to zero, with any leftover emissions being offset by atmospheric CO_2 removal efforts [281]. It is predicted that the Paris Agreement will be met by limiting the increase in global mean surface temperature to 1.5 degrees Celsius above pre-industrial values, mitigating some of the worst effects of climate change, and lowering the likelihood of reaching dangerous climate tipping points by attaining net zero emissions by 2050. Even while other greenhouse gas emissions, such as methane and black carbon, have a shorter half-life in the atmosphere than CO_2 emissions, they must be reduced in tandem with

CO_2 emissions to meet the 1.5 degC temperature target. This research study is a novel addition to the many paths being considered currently to reduce CO_2 emissions for the cement and concrete industry.

Chapter 6 – Summary, Recommendations, Future Research and Conclusion

This work is part of the Heidelberg Material Union Bridge Cement Plant's strategy to improve its operation to achieve self-defined excellence and thus is unique to the plant. The intent, however, is more ambitious. The goal is for the recommendations of this research to be adopted by the cement industry to help achieve the goal of reducing the environmental impact of cement manufacturing. Design experiments, data collected, analysis, and published results are all owned by Heidelberg Materials US.

6.1 Summary of Research

Chapter 1 gives the historical perspective of cement and how it has played a key role in civilization for over 6000 years. Together with stone and water, cement is one of the primary components of concrete. How has the history of concrete changed? Concrete became a more effective material over time. We transitioned from employing cement-like natural substances to improving natural materials through artificial procedures. Our techniques for making cement and concrete also evolved along with technology. Over 2,200 cement factories use a tremendous quantity of fuel, electricity, and limestone globally. Owners of cement plants are facing increasing pressure to reduce emissions to reap the benefits of more profitable and efficient facilities. They still have a long way to go, though. Over the past 30 to 40 years, there has been a significant global demand for cement due to the development of urbanization. Although this is excellent news for the sector, there are several environmental issues with cement production. Two aspects of defining the statement research questions are examined in this study. First, what effect does the growth and operation of the quarry have on society and the environment? The second query relates to the calcination of limestone in the kiln and preheat tower during the manufacturing process. Here is a definition of these questions:

1. Can improving kiln feed chemistry by consistent quarry material mix optimization help with the negative environmental impact of raw material demand and reduce waste dump stockpile size?
2. Can a machine learning algorithm be used to Predict CO_2 using a *Cement Manufacturing Historic Production Variables Dataset*?

Chapter 2 gives a step-by-step manufacturing process of cement making. It looks like the start of the process which is the quarry where most of the raw material for cement comes from. It describes the quarry development stage until the operation. This chapter goes into detail about the negative impact caused by quarry operations in the attempt to supply raw materials for cement manufacturing by reviewing existing literature publications. This includes the excessive extraction of limestone for cement manufacturing which affects the ecosystem and the land area; the impact of extraction of limestone on groundwater, and surface water; and the extraction of overburdened waste which is the byproduct of trying to get access to limestone, which is dumped as a stockpile; and the poor management of the overburdened stockpile. It also exposes the impact of the overburdened waste stockpiles on the ecosystem where large land mass is disturbed and covered with waste dumps affecting surface water. To reduce the material from the quarry to powdery material to feed the preheat tower and kiln, a raw mill is used. It also mentioned to meet the chemical reaction need, other materials are outsourced like sand to provide silicate, pounded ash to provide aluminum, and iron scales to provide the iron. The section also demonstrates how these problems mentioned herein related to the quarry operation can be addressed by raw material optimization. The raw material optimization will help deal with these problems mentioned herein related to the quarry operation and deal with outsourcing of sand which causes illegal sand mining.

The other component of the cement manufacturing process mentioned in Chapter 2 is the calcination process which results in the formation of clinker. This process starts at the preheat tower and finishes within the calcination zone in the kiln which involves the limestone as raw material and coal thermal heat for driving the chemical reaction. The literature review looks in detail at the multiple chemical reactions that occur during the calcination process to produce clinker which is later used as a finished product for cement milling. The by-product of these chemical reactions is the emission of CO_2 into the atmosphere. For years nothing was mentioned and there were no concerns regarding the emission of CO_2 until scientists discovered the devastating effect of the increase in CO_2 emissions on the world. With this finding an empirical formula was generated for cement plants to use to calculate the quantity of CO_2 emitted per ton of clinker produced. This empirical formula is complicated, difficult to use, and prone to error. In addition, the empirical only relies on limestone and thermal heat fuel source quantity. We hypothesize that these two factors are not the only things that affect the CO_2 generated but in addition to that, the asset performance and process performance variables in the manufacturing of cement also affect the CO_2 generated. The manufacturing process is highly nonlinear since it relies on only two factors, but we must look at the total complexity of the cement manufacturing process. In addition, we believed that if we could show a strong correlation between asset and process performance variables with CO_2 then we can also predict CO_2. To test this hypothesis, we needed to collect asset and process performance data, perform sensitivity analysis, and then perform predictive analytics. This will be a novel phase to the understanding of CO_2 generation in cement manufacturing and give us an avenue for controlling the emissions during manufacturing.

Chapter 3 presents the different research methods adopted to address the research statement mentioned in Chapter 1 and expanded on in Chapter 2. To fulfill the raw material optimization solution mentioned in Chapter 2 which addresses problems related to the quarry development and operation, the following were designed and implemented to collect data at the quarry.

1. Modified a mining software (Supac) to generate optimized quarry scheduling which resulted in optimized blending chemistry data output. The exercise included block modeling, pit design, and mine scheduling.
2. Designed the data collection loop for the quarry to collect chemistry data during, the crushing operation
3. Designed the data displace system in the loaders for operators to control mix within the quarry during operation when loading haul trucks traveling to the crusher
4. Collected drilling blast hole samples for the lab analysis to calibrate chemistry data for the control loop and mining sequencing software
5. Statistical analysis of chemistry data using the software tool Minitab

To perform the sensitivity analysis using the asset and process performance variable data collected by monitoring the preheat tower and the kiln operation, the following experiments and research was performed.

1. I installed extra sensors and collected more “asset” and “process performance” data at the preheat tower and kiln. This was important to reduce errors in some of the data collected
2. Developed a machining learning tool to conduct the sensitivity analysis and predictive analysis
3. When comparing the prediction analysis produced by this research to the IPCC technique, it is more accurate. Additionally, the model is better at describing the source of the CO_2 reduction variable in the cement manufacturing process and representing the process functions of the cement production systems.

Chapter 4 presents the results of the analysis performed using the design experiment tools presented in Chapter 3. The results are presented concisely and objectively to answer the two research questions presented in Chapter 1. The Chapter goes in-depth with the statistical analysis of the chemistry data collected from the research methods described to show that the raw material optimization adopted in pit design and mining sequencing which resulted in a reduction of raw material usage and reduction on overburden waste stockpiles did not impact the quality of the raw material feed for cement manufacturing and even in some cases improved the quality of the mix in a way that outsources material like sand was reduced. The statistical analysis completed measures against the required chemistry targets required to be achieved by the quarry. Even the raw mill feed raw material was also evaluated and kiln feed material quality was also evaluated. In Chapter 4 in addition to the quarry, the results of the sensitivity analysis of correlating asset and process performance monitoring data of the preheat tower and kiln were generated statistically using machine learning. Different regression models were evaluated and predicted models were generated for CO_2 emission. It was demonstrated that it is the first time and a novel idea that will have an impact on the sustainability path of the cement industry toward NetZero by 2050.

Chapter 5 discusses the meaning of the results in Chapter 4. This chapter connects the results with the research study questions. The significance, relevance, and meaning of the findings are explored in detail in the discussion section. It focuses on providing an explanation and assessment of the findings, demonstrating how they connect to the topic of the dissertation and the literature review, and presenting evidence to back up your overall conclusion. The clear indication is the research methods adopted to allow for the optimization of raw materials at the quarry improving the use of overburden waste in the mix, improving pit design, improving mine scheduling, and having less impact on the environment and society. The same chapter ties the relevance of performing sensitivity analysis with performance with CO_2 emission during the calcination process. It discusses the results of the predictive analytics performed for CO_2 and how it plays a key role in the cement industry. It also discusses the research's impact on the cement industry and how it can be used to improve cement manufacturing in terms of operational excellence which intends to reduce the negative impact on groundwater, surface water, the ecosystem, social effect, and global warming

6.2 Recommendations

Machine learning approaches for CO_2 emission show promising results, but fitting data to a model is only one aspect of machine learning. To create a successful and trustworthy machine model, several steps must be carefully considered as mentioned in Chapter 3. Since the past cannot be changed, a trustworthy machine-learning model aims beyond simple historical prediction. Instead, the goal is to use machine learning to derive insights that will enable us to limit future results. There's a reason this technology is called machine learning: for the algorithm to continuously learn, it needs data. Therefore, is recommended that the model be trained with more data and errors limited. This means additional data is needed. Other machine learning techniques can also be adapted to better understand the models and to achieve better results. In addition to this, this study should be extended to other cement plants to compare results.

6.3 Future Research

The next phase of this research should focus on creating software that cement plants can simply link to their asset and process monitoring sensors for on-site CO_2 emission prediction. This software can be sold commercially. This will entail creating a computer application that enables a simple interface. Furthermore, to help lower CO_2 emissions and production output, the input-independent variables can be tested in a lab setting to observe their effects in real-time. This will necessitate the inclusion of crucial monitoring equipment in the arrangement that mimics actual clinker production operations. It is crucial to remember that, to maximize product quality and reduce environmental effects, managing kiln operations necessitates a comprehensive approach that considers several factors.

6.4 Conclusion

Cement production depends on the operation of quarries. The quarry is the main supplier of raw materials used in the manufacture of cement. Despite being crucial to the manufacturing of cement, little research is done to understand how quarry operations affect the environment and how much kiln feed quality influences clinker quality. Moreover, the cement industry has not adopted digitalization in the quarry or cutting-edge technology to improve operations. This research, the first of its kind to be published for the cement industry, shows how data management tools and modern technologies for regulated feedback loops can be used to optimize raw materials for quarry operations. Furthermore, utilizing data management control feedback loops to regulate mix design at the raw mill results in a significant quality improvement. The research shows a significant reduction in quarry overburden wasting, a reduction in the use of outsourced sand as an additive, a significant improvement in the quality of kiln feed, and the adoption of a data management architecture control loop feedback system when quarry modeling software tools are used for planning. The success of the research study is demonstrated by the results obtained. Currently, Heidelberg Materials US has implemented the same research findings in different quarries to achieve similar results.

Research is concentrated on creating commercially feasible technology to reduce greenhouse gas emissions as awareness of the need to avoid climate change grows. Examining the environmental and financial effects of process modifications targeted at cement production is essential, given the high energy consumption and carbon-intensive nature of the cement manufacturing industry. In the past, the amount of CO_2 emissions from the cement manufacturing process has been estimated using empirical equations that include some empirical numerical parameters. The cement manufacturing business is not one of the areas where artificial intelligence (AI) and machine learning techniques have made considerable progress in CO_2 prediction. The main objective of this study was to predict CO_2 emissions at the Heidelberg Material cement facility in Union Bridge by utilizing a new approach and machine learning technology. This enhanced the study's uniqueness for the sector. Using historical process data for the preheat tower and the kiln, where calcination results in CO_2 emission, a sensitive analysis with several input variables vs CO_2 emission tonnage was carried out to see the correlation with the total quantity of CO_2 emitted. Predictive analytics models were also run using the data. Despite being relatively new to the cement industry, artificial intelligence (AI) and machine learning have demonstrated the ability to help this sector understand the total quantity of CO_2 emitted. The results showed that two variables had the strongest correlation with CO_2: (1) PRE-HEAT.STG 3 CYCLONE GAS OUTLET TEMP. [0–900 [_C]]; and (2) CONTROL FOR KILN MAIN DRIVE SPEED.

What are the advantages of this novel study methodology? By proving its practicality, this technique can help replace the laborious approach now used to calculate the amount of CO_2 emitted during cement making. Remarkably, the current mythology requires three separate belt scale calibrations: one to measure the amount of raw material used in clinker manufacturing, one to measure clinker production about the quantity of limestone consumed, and one to measure the different fuel source tonnage used. Moreover, a detailed recording of the thermal heat content of every fuel source is necessary. All of these pieces of data are required to manually enter CO_2 emission data into a large spreadsheet calculator. Step audits are always required to guarantee that the numbers are obtained appropriately because the empirical method for calculating CO_2 involves numerous steps and may result in inaccuracies. However, our research study shows that now that the two variables required to achieve the same aims can be calculated using machine learning approaches, existing historical data may be easily employed to accomplish the same outcomes as the empirical technique, which requires a lot of labor. This will cut down on costs that could be used for other purposes. Furthermore, our study has unequivocally shown that, in the cement production industry, the two primary operational variables that have the greatest influence on CO_2 emissions are (2) KILN MAIN DRIVE SPEED CONTROL and (3) PRE-HEAT.STG.3 CYCLONE GAS OUTLET TEMP. [0–900 [_C]]. Because the model can lock with the data source for continuous feed, the new approach also helps with CO_2 prediction in advance. With this knowledge, laboratory tests involving the two variables can be carried out to track their impacts in real time and perhaps contribute to a reduction in manufacturing output and CO_2 emissions. Lowering the CO_2 through asset performance controls and process monitoring variables allows the CCU's capital investment to be reduced because less volume needs to be captured. To explore the effects of changing the variables in such a system, necessary monitoring tools that replicate real-world clinker production seniors will be required. It is important to keep in mind that controlling kiln operations requires a complete approach that considers a variety of elements to maximize product quality and minimize environmental effects. Such studies cannot be conducted in real time on the production facility due to the numerous reactions that may occur, as there could be substantial detrimental repercussions. It is rather clear from this study that machine learning, artificial intelligence, and digitization will someday be required in the cement sector. The industry has a plethora of historical data that may be used to learn how the process could be improved to reduce CO_2 emissions. The industry must quickly use machine learning and artificial intelligence (AI) capabilities to improve manufacturing efficiency and lessen its environmental impact. The machine learning and AI, in turn, will suggest new sensing modalities and distributions in a (hopefully) virtuous cycle.

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