DISSERTATION

ENGINEERING OF INTELLIGENT SYSTEMS FOR SUSTAINABLE CEMENT MANUFACTURING

Submitted by

Olurotimi Oguntola

Department of Systems Engineering

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Doctoral Committee:

Advisor: Steve Simske

Kamran Eftekhari Shahroudi
Erika Gallegos
Francisco Ortega

ABSTRACT

ENGINEERING OF INTELLIGENT SYSTEMS FOR SUSTAINABLE CEMENT MANUFACTURING

Cement-based materials have been used for urban development from historic times, remain important till the present day, and will be required for construction in the foreseeable future. However, cement manufacturing by its nature is carbon-intensive and consumes a lot of energy. The cement industry faces significant challenges in implementing sustainable practices and reducing its environmental footprint. Carbon dioxide emissions from global cement production have increased at a higher rate than cement production rates. While traditional carbon reduction efforts have focused on thermal energy use in the calcination process of cement manufacturing, electrical energy consumption represents a substantial but often overlooked opportunity for sustainability improvements. This dissertation employs a systems engineering approach to address this gap by developing intelligent systems for sustainable cement manufacturing with a focus on decarbonization through electrical energy consumption optimization.

Through systematic review of research published between 1993-2023, life cycle assessment, and techno-economic analysis, this study demonstrates that substantial environmental and economic benefits can be achieved through innovative approaches. Analysis of four scenarios from a combination of two cement types (ordinary Portland cement, Portland-limestone cement) and two energy sources for thermal heating (coal, dried biosolids) indicates that increased production and adoption of Portland-limestone cement with up to 15% limestone can reduce carbon footprints by 6.4%, while using dried biosolids as combustion fuel can yield a 7.9% emission reduction compared to baseline. More significantly, the application of a memory-efficient hybrid variant of Causal Bayesian Optimization (CBO) to raw meal grinding indicates potential specific electrical energy consumption reductions of 26.7%.

The study also introduces an IoT-inspired deployment framework for continuously assessing environmental and economic impacts and proposes that with Industry 4.0 digitalization and advancements

in data analytics, artificial intelligence can extract operational insights from plant sensors and meters. This presents a cost-effective, high-return, and low-risk opportunity to optimize electrical energy consumption in cement manufacturing. By understanding causal relationships between cement plant system components and implementing targeted interventions to optimize electrical energy consumption in the production process, cement manufacturers can significantly contribute to decarbonization efforts, improve sustainability and resource efficiency, and enhance profitability and public image.

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This dissertation represents not only years of academic pursuit but also the unwavering support of remarkable individuals who stayed with me on this journey. To my advisor Dr Steve Simske, whose intellectual guidance, patience, and immense knowledge challenged me to exceed my own expectations – I am profoundly grateful for your mentorship.

I extend sincere appreciation to my academic committee members, Dr. Kamran Eftekhari Shahroudi, Dr. Erika Gallegos, and Dr. Francisco Ortega, for their willingness to share their expertise, invaluable insights, and guidance throughout this project. I also want to thank the program coordinator Ingrid Bridge and the Systems Engineering department for having answers to all the questions throughout the program.

My gratitude goes to my wife, Arinola Oguntola, whose love, sacrifice, and understanding provided the support needed for this journey. And to my children, Oluwatumininu Oguntola, Firekunmi Oguntola, and Fayokunmi Oguntola, who filled this journey with joy and perspective – you are the perfect reminders of what truly matters.

This accomplishment belongs to all of us. To God be the glory!

DEDICATION

To my father, Joel Oguntola, the first engineer I ever knew, and the loving memories of my mother, Ruth Oguntola, who would have wanted to witness this.

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Chapter 1 - Introduction

1.1 Global Cement Production and Environmental Impact

Cement-based materials are essential for urban development, with a rich history dating back to the Egyptian pyramids (3000 BC) and Roman architecture (300 BC-476 AD). Joseph Aspdin's invention of Portland cement in 1824 revolutionized construction and enabled landmark structures from the Alvord Lake Bridge (1889) to the Hoover Dam (1936) and modern skyscrapers. However, this essential material comes with significant environmental consequences.

Growing awareness of the importance of mitigating climate change drives research efforts toward developing economically viable technologies for reducing greenhouse gas emissions. The high energy consumption and carbon-intensive nature of cement manufacturing make it worthwhile to examine the environmental and economic characteristics of process improvements in cement production. Climate change and further warming due to greenhouse gases in the atmosphere can significantly impact life. Its effects include frequent and severe storms, wildfires, floods, heavy precipitation in some regions and severe drought in others, rising sea levels, and impacts on health, food, and water supply.

Cement production has more than doubled since 2000, with urbanization and infrastructure development continuing to drive demand upward. Global cement production reached approximately 4.1 billion tons in 2022, with China accounting for more than half of the worldwide output [1-2]. Cement production is estimated to be responsible for approximately 8% of the global carbon dioxide (CO_2) emissions caused by humans [3]. From the statistics in Figure 1 and Figure 2, these emissions have shown a troubling trend, increasing faster than the cement production rate, indicating a worsening carbon intensity in some regions.

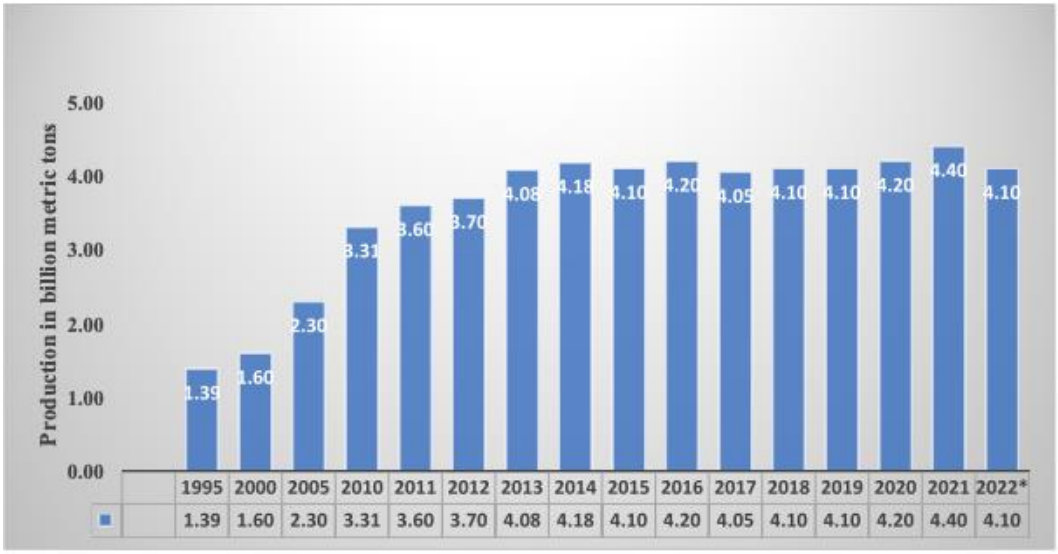

Figure 1: Cement production worldwide from 1995 to 2022 [4]

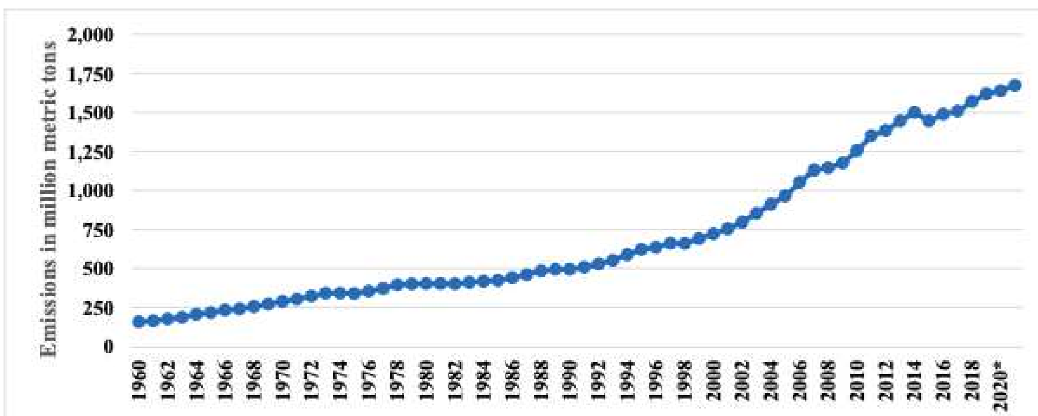

Figure 2: Carbon dioxide emissions from the manufacture of cement worldwide [5]

1.2 Carbon Footprint of Cement Manufacturing

Cement production has three stages: raw material extraction and preparation, clinker production, and cement grinding. First, limestone ($CaCO_3$) is ground with other minor constituents and heated at 900°C via cyclones. The mixture is passed through the rotary kiln to produce a mixture of calcium silicates (cement clinker) from reactions at 1450–1500°C. The clinker is cooled, ground to a fine powder, and mixed with gypsum to produce cement [6]. Cement manufacturing is inherently carbon-intensive due to chemical and energy-related emissions. Carbon dioxide is a by-product of the chemical conversion process that produces clinker from limestone and clay. This reaction represented as $CaCO_3$ + Heat → $CaO + CO_2$, accounts for approximately 60% of emissions in cement production. The remaining emissions come from burning fossil fuels to heat the kiln to the extreme temperatures (1450-1500°C) required for clinker formation and from generating the electricity that powers various manufacturing processes.

Reports from major Western cement manufacturers such as LafargeHolcim and Heidelberg Cement indicate that more than 550 kg of CO_2 is emitted per ton of cement produced. However, due to the high temperatures required for its production and the direct emissions from the calcination of limestone, decarbonizing cement production is challenging and has been the subject of many research efforts [6-8].

1.3 Current State of Energy Consumption in Cement Production

The cement industry uses 12-15% of the global industrial sector's annual energy consumption, highlighting its significant energy footprint [9]. This considerable energy use contributes to approximately 8% of global CO_2 emissions. Because of the cement industry's environmental impact, specific mitigation strategies, such as using alternative fuel and clinker substitution, are required. There are opportunities to mitigate CO_2 emissions from process modification and energy efficiency because both process- and fuel-related emissions account for approximately 40% of total direct emissions. Some CO_2 mitigation methods suggested in the literature include carbon sequestration or carbon capture, utilization and storage (CCUS), use of alternative fuels in the kiln, energy recovery, waste heat recovery, and increasing the proportion of semi-dry and dry processes [10].

Energy consumption in cement manufacturing falls into two major categories: thermal and electrical energy. Thermal energy, primarily used in pyro-processing for clinker production, accounts for approximately 70-80% of total energy consumption. The International Energy Agency reported that, from 2010 to 2020, the thermal energy intensity of clinker decreased by 0.2% annually. However, it has since plateaued at around 3.6 GJ/t. This decline brought about a rise in the sector's electricity intensity, estimated at 100 kWh/t cement since 2022 [11].

Electrical energy drives crushing, grinding, conveying, and machine operation throughout the manufacturing process of cement. A typical modern cement plant is estimated to consume up to 110 kWh of electricity for grinding a ton of cement [12]. About 95 million metric tons of cement was produced in the United States in 2022, using up more than 8.9 billion kWh of electricity with resultant emissions of an estimated 4.47 million tons of CO_2 by the power plants which typically use fossil fuel or natural gas to generate the electric power used for manufacturing [13].

1.4 Research Gap in Electrical Energy Consumption Optimization

The strategies for carbon-reduction process improvements in energy use within cement manufacturing have been largely focused on thermal energy despite the significant carbon emission contribution from electrical energy consumption (EEC) during production [13]. Research findings indicate that adopting some of the advancements in thermal energy efficiency in cement production increased EEC within the sector. The cost of cement production rises directly with the price of electricity. EEC in raw meal grinding is a critical aspect of cement production, where grinding operations can account for up to 27% of total plant electricity demand [14]. The energy required for grinding operations represents one of the largest operational costs in this industry, directly impacting production efficiency and sustainability metrics. This emphasizes the value obtainable from optimizing EEC in the raw meal grinding process of cement manufacturing.

Despite its obvious importance, research on implementing electrical energy-saving measures at the plant level has been surprisingly slow. The literature search indicates that studies on power consumption optimization in cement manufacturing are limited in number and scope [13]. This presents a significant research gap that this dissertation aims to address.

1.4.1 Limitations of Conventional Optimization Approaches

Implementing optimization within the complex system of raw meal grinding is quite challenging. The challenges primarily revolve around the complexity of the grinding process and the requirements for accuracy in modeling. The nonlinear nature of grinding, coupled with variable working conditions, complicates the establishment of effective mathematical models for optimization. Advanced modeling techniques are being developed to optimize grinding parameters and improve throughput [15]. However, many efforts are not focused on improving the energy efficiency of the raw meal grinding process.

Traditional optimization approaches using a simple machine learning model of a cement plant have not resulted in sustainability practices at the cement plant because they have struggled to fully address the inherent complexity and nonlinearity of the raw meal grinding process. The outcomes of typical traditional optimization have been difficult to translate to actual interventions at the cement plant.

1.4.2 Need for a Different Approach

Unlike simple ML models operating in optimization loops that treat process variables as independent inputs without understanding causal relationships, cement manufacturing requires understanding why parameter changes affect electrical energy consumption. Listed under are limitations with traditional optimization approaches that make them sub-optimal for optimizing electrical energy consumption in the raw meal grinding system of cement manufacturing:

- Not distinguishing between correlation and causation in complex industrial systems.
- Failing to account for confounding variables and material variations.
- Difficulty in ascertaining that their interventions will not violate physical constraints or quality requirements.
- Difficulty in handling the significant disturbances (such as noise, environmental factors, material variations, and human interactions) inherent in real-world manufacturing.

1.5 Systems Engineering Approach to Sustainable Manufacturing

Addressing the complex challenges of sustainable cement manufacturing requires a comprehensive systems engineering approach. Systems engineering principles provide a framework for bringing systems into being, encompassing system synthesis, analysis and evaluation, system life-cycle engineering, and implementation. This approach is particularly valuable for tackling the multifaceted problem of optimizing electrical energy consumption in cement production while maintaining product quality and economic viability.

The cement production system can be decomposed into ten interconnected subsystems. Figure 3 shows this decomposition and estimates the specific electrical energy consumption (SEEC) within each subsystem.

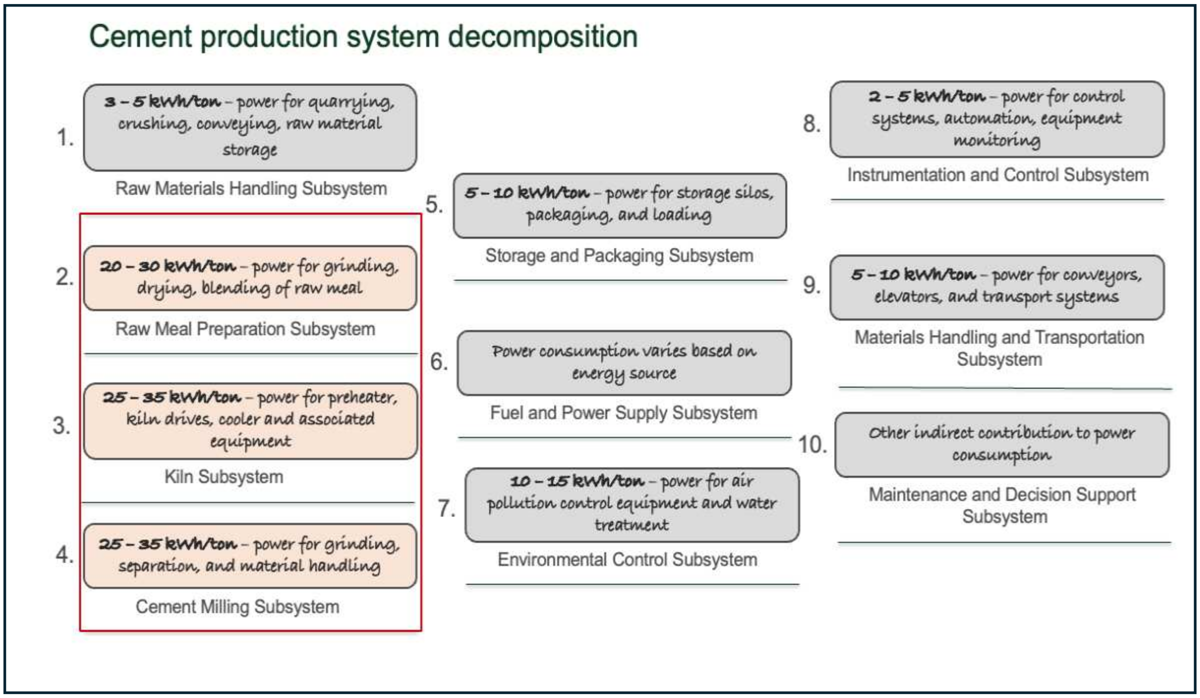

Figure 3: Cement production as a system of systems

A system of systems (SoS) engineering approach enables the integration of these subsystems into a cohesive whole. SoS engineering is defined by distinguishing characteristics and views a system-of-systems as a network whose engineering can benefit from network management best practices [16]. This perspective is essential for understanding the interconnected nature of cement manufacturing processes and identifying opportunities for optimization across subsystem boundaries.

With the advent of Industry 4.0 and the industrial Internet of Things (IIoT), there are new opportunities to apply advanced technologies to cement manufacturing. Digitalization and data-driven process optimization of cement manufacturing will help the industry better manage energy consumption and reduce emissions and raw material inefficiencies [17]. There has been improvement in sensors, data management, related Internet of Things (IoT) toolkits, and increased maturity levels of artificial intelligence. These and the templatization of life cycle and techno-economic assessments all contribute to a deployment framework for continuously assessing the economic and environmental impact of process improvements in cement manufacturing [18].

1.6 Goals, Research Questions, and Contributions

The main objective of this research is to determine if operational data from a cement manufacturing system can be used to engineer systems to reduce carbon emissions in the cement manufacturing process while maintaining product quality and economic viability. The scope of the study includes how to leverage advanced analytics, industrial Internet of Things (IIoT), and systems engineering principles to develop methods for sustainable cement manufacturing process improvements.

To accomplish the goal, research questions were identified as follows:

- How can causal relationships between operational variables be systematically identified and leveraged in cement raw meal grinding optimization, where traditional ML approaches fail due to confounding variables and complex interdependencies?
- What framework can effectively handle the significant real-world disturbances (material variations, environmental factors, equipment degradation) that render conventional optimization approaches inadequate in industrial cement manufacturing?
- How can Causal Bayesian Optimization be adapted to complex, real-world industrial systems with operational constraints, quality requirements, and safety considerations?

The hypothesis is that proper analysis of the cement plant operational data by leveraging advanced analytics and systems thinking can result in process improvement recommendations for the cement industry. More specifically, this research represents a significant advancement in industrial optimization by:

- Introducing the first comprehensive causal framework for industrial energy optimization that goes beyond correlation-based approaches to understand true cause-and-effect relationships in manufacturing systems.
- Creating a generalizable systems engineering framework that integrates environmental impact assessment and economic viability analysis of process improvements to help cement manufacturers make informed decisions that balance sustainability and profitability.
- Address a critical gap in sustainable cement manufacturing by focusing on optimizing electrical energy consumption, which has received less attention than thermal energy improvements despite its significant environmental impact.
- Pioneering the application of causal inference and Bayesian optimization techniques in heavy industrial settings to reduce electrical energy consumption in the raw meal grinding subsystem of cement manufacturing, extending CBO to complex manufacturing environments with multiple constraints and disturbances.

1.7 Dissertation Structure

This dissertation addresses the critical challenge of optimizing electrical energy consumption in cement manufacturing through the engineering of intelligent systems. It builds upon the author's published research papers, which provide a foundation for understanding the environmental impact, economic viability, and technical approaches to sustainable cement production.

The dissertation is organized as follows:

Chapter 2 reviews literatures and existing methods of decarbonization and optimization, establishing the framework for exploring how intelligent systems can contribute to sustainable cement manufacturing. Chapter 3 presents a continuous assessment framework for environmental impact and economic viability of sustainability improvements based on life cycle assessment (LCA) and techno-economic assessment (TEA) methodologies. This chapter examines four scenarios from a combination of two cement types and two energy sources for thermal heating, demonstrating the potential for significant emission reductions.

Chapter 4 explores artificial intelligence applications for electrical energy consumption optimization, synthesizing existing scholarly works and industry reports on methods and approaches for EEC optimization in cement production. It highlights the value of applying artificial intelligence to extract operational insights from data collected at cement plants. Chapter 5 presents experimental validation and results from implementing a novel approach. It focuses on applying a memory-efficient hybrid variant of Causal Bayesian Optimization to raw meal grinding, which demonstrates the potential for substantial reductions in electrical energy consumption. Chapter 6 concludes the dissertation by summarizing the research findings and contributions, discussing implications for sustainable manufacturing, acknowledging limitations, and suggesting directions for future research.

Through this structure, the dissertation aims to contribute to the ongoing efforts to decarbonize cement manufacturing by addressing the significant but often overlooked opportunity of electrical energy consumption optimization.

Chapter 2 – Literature Review and Existing Methods

A peer-reviewed publication [18] previously addressed the literature review and discussion of existing methods for sustainability in cement manufacturing. This chapter includes an updated version of part of that publication. It also consists of a literature review of existing methods of causal inference optimization, which has been addressed in another paper submitted for publication by the author.

2.1 Literature Review: Cement Manufacturing and Sustainability

According to a World Economic Forum publication in 2024, cement manufacturing remains one of the most significant industrial contributors to global greenhouse gas emissions [19]. Demand for cement is expected to increase as the need for infrastructure development continues to expand in emerging markets. The tension between increasing construction needs and decarbonization goals creates a significant sustainability dilemma. As a result, the decarbonization of the cement manufacturing process has received research attention, and there is a lot of literature on CO_2 mitigation methods.

2.1.1 Environmental Impact Factors in Cement Production

The environmental impacts of cement manufacturing span across multiple dimensions and create a complex sustainability challenge that requires a systems approach to address effectively. As already identified, carbon emissions remain a challenge. Despite innovations in production methods and the development of alternative materials, the fundamental chemistry of cement production makes complete elimination of emissions challenging without carbon capture.

Another factor is the energy consumed in the manufacturing of cement. Substantial thermal energy is required for clinker production, and electrical energy is needed for grinding operations, motors, and material movement and separation equipment. Fossil fuels are the sector's main source of thermal energy and make up about 90% of the energy mix. At the same time, bioenergy, renewable, and non-renewable waste make up the balance [11]. While electrical energy consumption is smaller in absolute terms than thermal

1. This chapter includes part of the publication: Oguntola, O., & Simske, S. (2023). Continuous Assessment of the Environmental Impact and Economic Viability of Decarbonization Improvements in Cement Production. Resources, 12(8), 95. https://doi.org/10.3390/resources12080095

energy consumption, it is still substantial, requiring 90-110kWh per ton of cement. In many regions where cement is manufactured, electricity is also generated from fossil fuel sources, further contributing to the carbon footprint of cement production.

Other environmental impact factors of cement manufacturing include raw material consumption, water and pollution, air and particulate emissions, waste generation and management, land use, and ecosystem impacts [20]. Cement production places a lot of demand on natural resources, particularly limestone, the primary raw material. Water is used in cement manufacturing for cooling equipment, controlling dust, and processing materials. Apart from greenhouse gases, cement manufacturing also generates other air pollutants (dust, nitrogen oxides, sulfur oxide, carbon monoxide, etc.) that affect local air quality and human health. Cement production creates waste such as kiln dust, bypass dust, and rejected materials, some of which cannot be recycled and require waste disposal. Cement plants and associated limestone quarries take up large land areas, potentially leading to habitat loss, deforestation, and landscape alterations.

2.1.2 Current Sustainability Approaches

The decarbonization pathways in the cement industry include replacing clinker with supplementary cementitious materials, alternative chemistries and processes to replace limestone from the clinker production process, fuel switching and electrification, and carbon capture.

Cement companies can leverage carbon capture and storage (CCS) technologies to capture CO_2 from significant point sources in their manufacturing process or the atmosphere, transport it, and store it permanently underground. The paper in [21] examined limitations in deploying CCS technologies despite their availability and maturity. The authors advocate for expanding government policies to incentivize the adoption of CCS and mandate its deployment.

Using alternative fuels properly can reduce the cement industry's environmental impacts. Related research has advanced, indicating that introducing solid waste materials as alternative fuels in cement manufacturing will lower energy consumption and reduce greenhouse gas emissions. By coupling the cement and waste management industries, solid waste materials such as municipal solid waste, sewage sludge, biomass, end-of-life tires, and meat and bone animal meal can be considered alternative fuels to replace or reduce the consumption of non-renewable fossil fuels in cement manufacturing [22].

More cement factories are now leveraging Waste Heat Recovery (WHR) systems to achieve energy performance as required by standards and legislation. The waste heat from the kiln is used as a power generation source, thus reducing thermal energy losses and improving the energy efficiency of the cement manufacturing process. In [23], the authors evaluated the performance of a WHR system, comparing it to the estimated performance from feasibility studies and proved positive financial indicators by comparing actual to updated capital expenditures. In addition, energy efficiency can be improved in cement production by leveraging process control and management systems, high-efficiency motors and drives, and efficient grinding technologies.

The process routes for cement manufacture are dry, semi-dry, semi-wet, and wet. The wet processes consume more energy than the dry processes. While the choice of process is primarily determined by the availability of raw materials, with expansion and significant improvements in the cement plant, semi-dry processes can be changed to dry processes to reduce GHG emissions [10].

Table 1 summarizes decarbonization methods in literature, the materials and equipment used, and cost examples where available.

2.1.3 Limitations to Sustainability Approaches in Cement Manufacturing

The referenced publications [13,18] by the author cover key limitations of current sustainability approaches in cement manufacturing, and they are highlighted below:

2.1.3.1 Technical and Process Limitations

1. Process emissions inherent to traditional chemistry: Approximately 60% of cement production emissions come from the calcination process itself, making them difficult to eliminate without fundamental changes to cement chemistry or using carbon capture technologies.

Table 1 Decarbonization methods

Method	Decarbonization Lever	Materials/ Equipment	Process Summary	Cost Example	Reference
Methods increasing the process energy efficiency - Process Decarbonization					
Introduction of energy efficient clinker technology with low cooling air requirement	Process Decarbonization	Modern grate clinker coolers	Optimization of clinker coolers	Varies due to site specifics	[24]
Waste heat recovery		Boiler/turbine system	Waste heat used for drying, steam production, or feeding local heat network. Decrease of 4 -15 kg CO_2/t clinker	Depends on local power prices	
Replacing long wet/ semi-dry kilns with energy efficient pre-heater/pre-calciner kilns		Construction may be required	Raw material lower moisture content. Additional cyclone stage. Thermal energy decreases of 900 - 2800 MJ/t clinker. Electrical energy decreases of 0 -5 kWh/t clinker	35M - 50M EUR investment. 2.85 - 9.2 EUR/t clinker decrease in operating cost	
Methods utilizing alternative fuels - Circular Economy E.g. Solid wastes, different biomass sorts, fuels with lower heating values	Circular Economy	Sewage sludge, wood waste, grain rejects, animal meal, mixed industrial waste, waste oil, tires, plastics	Use for combustion in pre-calciner vessel. Integrate into waste management. Processing compliant with international environmental agreements and local policies	Investment costs for storage, handling, pretreatment. Lower operational costs. 15 - 30% of coal price in Europe.	[24]
Methods utilizing different raw materials to reduce emissions from limestone decomposition - Circular Economy	Circular Economy	Already decarbonated materials E.g. Metallurgical slags, coal ashes, concrete	Limits process related and fuel related CO2 emissions	Limited availability of materials	[24]

		crusher residues			
Decarbonization strategies - Process Decarbonization					
Post-combustion capture. Decarbonizes flue gases generated from total oxidation process	Process Decarbonization	Solvents that react with CO_2 e.g. MDEA, MEA, DEA, AMP, PZ*	CO_2 absorbing reaction, heat to reverse absorption, moisture removal, compression, transportation, storage/utilization	$50.6/ton [25]	[26]
		Natural and synthetic calcium-based sorbents			
		Polymeric membranes	Compress flue gas, pass through stages of membranes and compression to capture CO_2,		[27]
Pre-combustion capture. Decarbonizes syngas resulting from fuel partial oxidation process before combustion		Synthetic gas from feed stock (e.g. coal), steam, air, heat	Water-gas shift reaction, CO_2 capture, separation, transportation, sequestering	$60/ton capture cost	[28]
Oxy-combustion. Uses oxygen rather than air for fuel total oxidation		Oxygen-rich medium	Fuel combustion in pure or enriched oxygen stream	60 - 70 EUR/ton CO2 avoided cost	[29]
Other methods					
Electrification and Renewable Procurement - Clean Energy	Clean Energy	Synchronous power such as hydropower and biomass. Variable generation such as wind and solar	Reusability, recyclability, product longevity.	Varies by site. Influenced by the price and availability of zero-carbon electricity	[30]
Eco planet and Efficiency Gains in Construction - Carbon Efficient Construction	Carbon-efficient Construction	Design and engineering techniques to reduce amount of concrete required	Examples: curved fabric molds, pre-stressed concrete using tensioned steel cables. Concrete mixture optimization.	Varies.	

* MDEA - Methyl-Di-Ethanol-Amine   DEA - Di-Ethanol-Amine   AMP - 2-Amino-2-Methyl-1-Propanol   PZ - Piperazine

2. Energy efficiency plateaus: According to an International Energy Agency Report, the intensity of thermal energy use has plateaued at around 3.6 GJ/t after initial improvements, suggesting conventional efficiency measures are reaching their limits [11].
3. Contradictory optimization effects: Some thermal energy efficiency advancements have increased electrical energy consumption, creating a trade-off rather than a net sustainability gain.

2.1.3.2 Implementation and System Integration Challenges

1. Capital-intensive infrastructure requirements: Many sustainability approaches require significant capital investments with extended payback periods, thus creating financial barriers to adoption, especially for aging cement plants.
2. Siloed approaches: The overall effectiveness of current sustainability methods is often limited because they focus on isolated aspects of production rather than viewing cement manufacturing as an integrated system.
3. Limited data utilization: Despite the potential of IoT and digitalization, there's a gap in effectively utilizing operational data for optimization. Many cement plants fail to collect and store operational data and do not invest in technical resources, resulting in a lack of leverage of advanced analytic capabilities.
4. Inconsistent measurement frameworks. Standardizing environmental impact measurements across different production scenarios, technologies, and geographical regions presents challenges.

These limitations collectively point to the need for more integrated, system-based approaches that combine technological innovations with advanced analytics and consider environmental and economic factors within a unified framework.

2.1.4 Systems Perspective on Cement Manufacturing Sustainability

In addition to process improvements, a comprehensive systems approach to cement manufacturing sustainability considers the entire production value chain. Its scope covers from raw material extraction to end-of-life considerations. This perspective considers the interconnections between various subsystems and stakeholders in the cement ecosystem. Within this view, concepts like circular economy, industry 4.0, and digital technologies are powerful tools for implementing this systems approach to sustainability [31]. These technologies can help manage the complex trade-offs between environmental impact, product quality, and economic viability central to sustainable cement manufacturing.

2.2 Literature Review: Optimization Methods in Cement Production

Optimizing energy use in cement production has become an imperative rather than an option for manufacturers. The cement manufacturing industry faces dual pressures of economic competition and environmental sustainability. Cement manufacturing optimization spans multiple objectives: reducing energy consumption, minimizing emissions, maintaining product quality, maximizing production efficiency, and ensuring economic viability.

2.2.1 Evolution of Optimization Approaches

Literature on cement production optimization has evolved over the past two decades to reflect technological advancements, analytical methods, and sustainability priorities. More recent literature has gone beyond just focusing on mechanical and thermal efficiency improvements through equipment upgrades and process modifications to following electrical energy optimization within several key themes: "automation and process control, power generation from waste heat recovery systems, digitalization and application of artificial intelligence" [13]. The advent of Industry 4.0 technologies enables more sophisticated optimization methods to handle the complex, nonlinear relationships and multiple objective characteristics of optimization in cement manufacturing.

2.2.2 Scope and Organization of Literature Review

Chapter 4 of this dissertation is an update on the author's publication of a systematic literature review that synthesizes and analyzes existing scholarly works and industry reports on general methods and approaches for electrical energy consumption in cement production. Optimization methods are evaluated for their theoretical soundness and practical applicability in cement production plants. Consideration is given to implementation challenges, data requirements, and demonstrated benefits.

The literature review in this chapter is restricted to methods for optimizing EEC through the lens of 'causality' – the idea that one event or action can lead to another event or outcome. This lens identifies more accurate interventions and enables a better process understanding by examining direct causal relationships, indirect causal paths, and confounding variables. It covers causal inference and Bayesian optimization methods that explicitly model causal relationships between process variables, enabling more effective interventions. The interventions can be applied directly to operation parameters at the cement plant to realize a measurable reduction in electrical energy consumption.

2.2.3 Optimization Methods

Leveraging causal inference and Bayesian statistical methods would be effective in determining the measures of operational parameters that would yield optimal EEC, especially in the raw meal grinding subsystem of the cement production system. The methods' applications suggest their effectiveness for decision-making in this scenario, where understanding cause and effect is crucial, and interventions can be applied to attain reduced levels of EEC at the cement plant.

2.2.3.1 Iterative Causal Inference

Iterative Causal Inference (ICI) leverages causal relationships among variables to optimize complex systems. It's a methodology that enhances understanding underlying dynamics and improves decision making. ICI employs causality-based learning to identify model structures and recover unobserved variables, making it more resistant to random noise than purely data-driven methods [32]. The algorithm creates mathematical models to estimate variables that can't be directly observed and treats these estimates as if they were actual measurements. It focuses on local relationships between variables while incorporating known constraints and leverages specialized techniques to prevent mathematical instabilities. The approach leverages iterations that refine causal graphs based on conditional independence tests. Rohekar, Raanan Y., et al. [33] present a comprehensive paper on the iterative causal discovery algorithm for recovering causal graphs when there are latent confounders and selection bias. This approach assumes a directed acyclic graph (DAG) for the underlying causal structure and focuses on learning it from observational data.

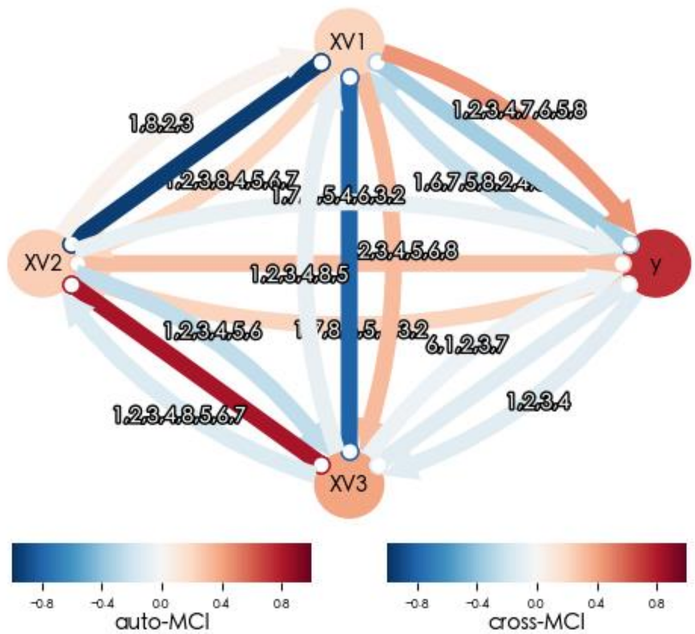

Figure 4: Network visualization of causal relationships in the raw meal grinding process

Figure 4 plots the causal relationships between EEC (Y) and the multiple variables of the raw meal grinding system after dimension reduction to 3 variables (XV1, XV2, XV3) with the partial least square regression algorithm. Process variables are nodes, and the causal relationship is depicted as arrows in the diagram. The colors of the arrows indicate relationship strengths.

Structural vector autoregressive (SVAR) processes, which are often employed in causal inference when modeling time series data, can be rephrased as a linear Structural Causal Model (SCM) of stochastic processes on a simple causal graph [34]. Peters et al. [35] provide a generalized definition of structural causal models in their study of causal models for dynamical systems.

Suppose a structural causal model (SCM) of the raw meal grinding system is defined as

$$M = (X, U, f, P(U)) \tag{1}$$

where:

- $X = \{X_1, X_2, \ldots, X_N\}$ are observed variables in the raw mill grinding data (e.g., limestone flow rate (T), raw mill motor (kW))

- $U = \{U_1, U_2, \ldots, U_N\}$ are exogenous variables (unobserved)
- $f = \{f_1, f_2, \ldots, f_N\}$ are causal mechanisms
- $P(U)$ is a probability distribution over U

Each variable is determined by $X_i = f_i(Pa(X_i), U_i)$, where $Pa(X_i)$ are parents of X_i in the causal graph [36]. Iterative causal inference combines causal discovery with optimization in a step-by-step iterative process as follows:

1. Causal Discovery. At iteration t in the causal discovery step, estimated causal effects are given by:

$$\tau_i^{(t)} = E[Y|do(X_i = x_i + \delta)] - E[Y|do(X_i = x_i)] \quad (2)$$

Using Python programming language, this is estimated with a method like Double Machine Learning [37, 38]:

$$\tau_i^{(t)} = \frac{E[\left(Y - E\left[Y\middle|X_{\backslash i}\right]\right) \cdot \left(X_i - E\left[X_i\middle|X_{\backslash i}\right]\right)]}{E[(X_i - E\left[X_i\middle|X_{\backslash i}\right])^2]} \quad (3)$$

2. Optimization. Variables are updated based on causal effects:

$X_i^{(t+1)} = X_i^{(t)} - \eta . \tau_i^{(t)}$ where η is the learning rate

3. Constraint Application: $X_i^{(t+1)} = clip(X_i^{(t+1)}, X_{i,min}, X_{i,max})$

The causal effect τ_i indicates how changing variable X_i affects the target variable Y (EEC). If $\tau_i > 0$, increasing X_i increases Y. To make optimal adjustments to EEC, the update rule decreases variables with positive causal effects and increases variables with negative effects, moving toward lower EEC. The constraint application step captures the manufacturing requirements and limitations of the raw meal grinding system. In practice, constraint values can be obtained from subject matter experts, raw meal grinding equipment manuals, manufacturing process records, and the upper and lower-level bounds of the variables in historical data. As variables change, their causal effects may change due to nonlinear relationships. Re-estimating causal effects at each step addresses this.

Iterative causal inference offers robust frameworks for understanding causal relationships and optimizing a target variable by manipulating variables with direct causal relationships. Causal inference handles confounding and ensures adjustments are based on true causal relationships rather than spurious correlations. It also incorporates domain constraints. Its implementation provides statistical significance of causal effects and a clear interpretation of variable interactions. This gives it the key advantage over traditional optimization. However, it is important to recognize the limitations of assumptions of independence and the possibility of model misspecification, which can lead to biased estimates. This approach requires substantial historical data and is less adaptive to rapid system changes.

2.2.3.2 Causal Bayesian Optimization Framework

Causal Bayesian Optimization (CBO) is an advancement in the field of optimization that integrates causal inference with Bayesian Optimization (BO) frameworks. CBO is particularly useful in scenarios where understanding the causal relationships between variables can lead to more effective optimization strategies. It addresses a fundamental limitation in traditional Bayesian optimization: the inability to distinguish between correlation and causation in complex systems. CBO is apt for efficient and robust optimization in a domain such as raw meal grinding, where interventions have downstream effects and underlying causal mechanisms govern the relationship between variables. While CBO offers significant advantages, it requires efficient intervention strategies and has scalability challenges in high-dimensional settings. These challenges are being addressed through innovative algorithms and frameworks.

Researchers have recently adopted different CBO applications to enable optimization strategies. The architecture of the algorithms varies depending on the specific challenges they address. DAG recovery via Bayesian Optimization (DrBO) is a framework that utilizes Bayesian optimization to identify high-scoring DAGs from observational data [39] efficiently. The graph-agnostic CBO (GaCBO) algorithm outperforms traditional methods by integrating causal discovery as a subtask within CBO, addressing cumulative regret objectives in scenarios with unknown or partially known graphs [40]. High-dimensional CBO (HCBO) enhances optimization in complex scenarios by employing causal intrinsic dimensionality and a scalenormalized scoring function [41]. Constrained CBO (cCBO) optimizes target variables under constraints by reducing the search space using known causal graph structures and observational data. It models target and constraint quantities with Gaussian processes, selects interventions via a constrained expected improvement acquisition function, and balances fast convergence with feasible interventions [42].

The general algorithm for CBO is as follows:

1. Initialize with prior causal knowledge or learn the causal structure from observational data.
2. For $t = 1, 2, \dots, T$:
   a) Update the surrogate model (statistical model, often a Gaussian Process) based on observed data
   b) Estimate causal effects for candidate interventions
   c) Select the next intervention point by optimizing the acquisition function
   d) Apply intervention and observe the outcome
   e) Update dataset

In CBO, the optimization objective incorporates the causal effect of interventions: $x^* = \arg min_{x \in X}\ E[Y|do(X = x)]$ where $do(X = x)$ represents setting variables X to values x through intervention rather than mere observation. The surrogate model in CBO is built to approximate the interventional distribution $P(Y|do(X = x))$ rather than the observational distribution $P(Y|X = x)$.

CBO can use a linear regression approach for causal effect estimation:

$$\tau_j = E\left[Y\middle|do\left(X_j = x_j\right)\right] - E[Y|do\left(X_j = x_j'\right)] \quad (4)$$

Where τ_j is the causal effect of variable X_j on outcome Y

$do\left(X_j = x_j\right)$ represents the intervention of setting variable X_j to x_j

$E[\ ]$ denotes the expected value

Implementation is via backdoor adjustment:

$$\tau_j = \int E\left[Y\middle|X_j = x_j, Z = z\right].\ P(Z = z)dz - \int E\left[Y\middle|X_j = x_j', Z = z\right].\ P(Z = z)dz \quad (5)$$

$P(Z = z)$ is the probability distribution of the confounding variables, and Z represents the set of confounding variables. The integrals average over all possible values of the confounding variables.

The Gaussian process kernel [43] in CBO is a standard kernel with uniform length scales. The kernel function that measures similarity between points x and x' is defined as:

$$k(x, x') = \sigma_f^2 \exp\left(-\frac{1}{2}\sum_{j=1}^{d} \frac{(x_j - x_j')^2}{l_j^2}\right) \tag{6}$$

Where:

σ_f^2 is the signal variance (amplitude parameter)

d is the number of dimensions (variables)

x_j *and* x_j' are the j^{th} components of vectors x and x'

l_j are the length scale parameters controlling how quickly correlation decreases with the gap between different input points

CBO selects interventions via a standard expected improvement acquisition function, uses simple boundary constraints, and uses a standard Bayesian optimization loop in its optimization process.

Standard Expected Improvement (EI) at point x is given as:

$EI(x) = E[\max(f(x) - f(x^+), 0)]$ and can be computed as

$$EI(x) = \big(f(x^+) - \mu(x)\big)\Phi(Z) + \sigma(x)\phi(Z) \tag{7}$$

Where $f(x)$ is the true objective function and $f(x^+)$ is the current best observed value. $\mu(x)$ is the mean prediction of the Gaussian process at x, and $\sigma(x)$ is the standard deviation of the Gaussian process prediction at x. $\phi(Z)$ represents the standard normal probability density function evaluated at Z.

Key components of CBO are listed below:

- Learning or identifying a causal structure. Some of the methods used include constraint-based algorithms [44,45], score-based methods [46], intervention-based approaches [47], and expert knowledge integration.

- Estimating causal effects. When all confounders are observed, an adjustment formula can be used, or methods like double machine learning and causal forests can be used [48].
- Modification of acquisition functions to account for causal information: causal expected improvement [42], causal upper confidence bound [49], and knowledge gradient with causal information [50].

CBO leverages the relationships between process variables to optimize EEC through interventions. This approach models complex dependencies and captures the dynamics of processes, facilitating more informed decision-making in the optimization task.

Limitations and Open Challenges - despite its advantages, CBO faces several challenges:

- Causal Discovery Uncertainty: Errors in causal structure learning can propagate to optimization
- Computational Complexity: Integrating causal inference with BO increases computational demands
- Limited Interventional Data: Many domains lack sufficient interventional data
- High-dimensional Spaces: Scaling CBO to high-dimensional spaces remains challenging
- Unobserved Confounding: Handling latent confounders in the optimization process.

There's an opportunity to tune an application of CBO to address some of these challenges.

Chapter 3 – Continuous Assessment of Decarbonization Improvements

3.1 Lifecycle Assessment and Techno-Economic Assessment

Lifecycle assessment (LCA) and techno-economic assessment (TEA) are often part of the validation for proposals of technologies aimed at reducing CO_2 emissions of industries, and carbon capture and utilization technologies are part of decarbonization options considered. When introducing new technology to reduce CO_2 emission, lower energy consumption, or capture and utilize carbon, it is imperative to perform LCA and TEA to ascertain the value added from the new technology or process change introduced. LCA aims to track the global environmental impacts of the production, use, and disposal of the product or service. TEA assesses the economic viability of the technology and is a tool for making decisions on research, development, investments, and policy.

Challenges with assessing technologies in their early stages result in an escalation of assessment efforts and potential mismatches of research results with the needs of stakeholders. To address this, [51] presented the best practices for adapting assessment methodologies to the technology readiness level (TRL) of the technology when assessing early-stage climate change mitigation CCU technologies. The authors advocate for meeting stakeholders' needs by aligning TEA/LCA goals and scope with TRL rather than commercial interests, estimating missing data using standard estimation tools, and evaluating and communicating uncertainties in the assessment. They also recommend collaboration across technology developers and TEA/LCA practitioners as a workaround for coping with limited resources. With consensus on technological measures for decarbonization, industry watchers advocate for coupling effective policy with a body of research on technical solutions to cement and concrete decarbonization [52]. More decisive policy actions will help promote the adoption of technological measures to decarbonize the cement industry. In addition, cement producers would benefit from a systematic way to continuously monitor and report the environmental impact of production processes to validate compliance with decarbonization policies as they adopt these technological measures.

The LCA and TEA in this study analyze emission and cost reduction opportunities from alternative manufacturing inputs in four different scenarios at a US cement plant. In addition, the study demonstrates a practical approach to integrating sustainability into cement manufacturing with a deployment framework for the continuous assessment of cement production's economic and environmental performance.

3.2 Materials and Methods

Digitalization and data-driven process optimization of cement manufacturing will help the industry better manage energy consumption and reduce emissions and raw material inefficiencies [17,53]. There has been improvement in sensors, data management, related IoT toolkits, and increased maturity levels of artificial intelligence. These, and the templatization of *lifecycle and techno-economic assessments*, all contribute to a *deployment framework* for continuously assessing the economic and environmental impact of process improvements in cement manufacturing.

Advancing innovative near-zero emission production routes, and promoting material efficiency, are two of the key carbon-cutting strategies that would contribute the most to direct emission reductions in the Net Zero Scenario [24]. Near zero or net zero emission production of cement would require incorporating carbon capture in the production process, thereby increasing the cost of production. However, significant carbon emission reduction is possible by promoting material efficiency. This study explores material efficiency options in demonstrating the deployment framework using the Union Bridge, Maryland plant of Lehigh Cement (LC) as a case study. Heidelberg Cement of Germany wholly owns LC and has affiliations with technically advanced cement operations and construction-related materials activities. LC's original plant was built in 1910 and has since undergone several modernizations, including replacing four long-dry kilns with one preheater/pre-calciner kiln system. At the time of this study, the LC plant in Union Bridge, Maryland, is transitioning from producing ordinary Portland cement to Portland-limestone cement, which uses innovative technology to increase limestone content and reduce clinker used. The product called EcoCem®PLC contains as much as 10% more limestone but performs equivalent to ordinary Portland cement in concrete compressive, flexural strength, and durability [54].

To demonstrate how the deployment framework can be leveraged for the continuous assessment and improvement of cement production's economic and environmental impact, we review its production at the LC plant in Union Bridge under four scenarios, as listed in Table 2 below.

Table 2. Cement production scenarios modeled

#	Scenario	Product	Thermal Energy
1.	OPC + Coal	Ordinary Portland Cement	Coal
2.	PLC + Coal	Portland-Limestone Cement	Coal
3.	OPC + DBS	Ordinary Portland Cement	Dried Biosolids
4.	PLC + DBS	Portland-Limestone Cement	Dried Biosolids

In the first two scenarios, thermal energy for producing ordinary Portland cement and Portland-limestone cement is provided by coal combustion. In comparison, in the other two scenarios, thermal energy is provided by the combustion of dried biosolids from processed sewage sludge. These scenarios were examined using the templates developed by the University of Michigan Global CO2 Initiative [55].

3.2.1 Lifecycle Assessment (LCA)

The international standard ISO 14040 defined LCA as a study of environmental and other potential impacts throughout a product's life. The product's life, often called ‘cradle-to-grave,' includes raw material acquisition, production, use, and disposal. Environmental impacts include resource use, human health, and ecological consequences [56]. A detailed assessment of the whole life of a product that serves as an input in another product can be complicated. As a result, many researchers in practice limit the LCA to the use phase, often called 'cradle-to-gate.' The concept of LCA is based on a simplified system analysis. Therefore, meaningfully selecting and defining system boundaries are important albeit labor-intensive tasks within the LCA process. LCA can be applied to product development and improvement, public policy making, strategic planning, and marketing, amongst other direct applications. The main parts of the LCA are –

- goal and scope definition (including functional unit and system boundaries)

- life cycle inventory (LCI)
- life cycle impact assessment (LCIA)
- interpretation

As defined by the ISO standard 14040, the scope and goal of the LCA have to be clearly defined and consistent with the intended application. The inventory analysis involves compiling and quantifying inputs and outputs required throughout the product lifecycle. The impact assessment component of the LCA aims to understand and evaluate potential environmental impacts throughout the product lifecycle. In the interpretation phase, conclusions are drawn from the inventory analysis and impact assessment, and recommendations are made to satisfy the study's objective.

LCA of cement manufacturing has been the subject of many research efforts [57-59]. In addition, different localized research efforts focus on the environmental impact of cement manufacturing in different parts of the world, including India, Brazil, Europe, and China. [60,61]. Leading international standards on LCA focus mainly on the process of performing LCA. Its principles and framework are described by ISO 14040, and ISO 14044 specifies requirements and provides guidelines [62].

Countries across the globe have also formulated a variety of standards and guidelines, such as the UK's PAS 2050 [63], France's BP X30-323, and Japan's EcoLeaf Environmental Labeling Program. However, the nature of a comprehensive life cycle analysis requires consideration of the inputs into the manufacturing process which often differ from one location to another. It also requires consideration of the context of each manufacturing plant's infrastructure, processes, policies, and quality control requirements. As a result, literature reviewed for LCA on cement manufacturing have varied in methodological approach and scope with each author articulating the environmental impact of cement production through differing lens based on their goal of doing the analysis. As indicated in Table 3, LCA is used to study the environmental impact of different lifecycle stages of cement production and usage, such as clinker, cement, mortar, and concrete.

In addition, literature review identified other materials that can be used as additives in cement manufacturing or in the mix of mortar and concrete to reduce the carbon footprints of the products. These materials and the resulting estimated reduction in GHG emissions from their use include the following: marble waste sludges in cement – 34% [64], ornamental stone waste in cement – 9% [65], blast furnace fly ash and slag in concrete – 32% [66], ash from wastewater treatment plant sludges in concrete – 9% [67], plastic waste and carbon fibers in cement mortars – 13.69% [68], and glass powder in cement mortar – 20% [69].

Practitioners agree that integrating LCA into day-to-day management routines will be beneficial, however, the execution of LCA is challenging. The LCA process can be kept simple without compromising comprehensiveness and reliability by using standard procedures and assumptions, adopting techniques that allow comparisons between different impact categories, access to high-quality data, and using adequate software [70]. Integrating LCA into management routines of cement plants has become feasible with international standards for LCA through the ISO process, increasing the number of cement plants getting more digitized and adopting IoT sensors for gathering data, and improved interconnectivity and access to databases through application programming interfaces (API). Section 2.3 demonstrates a theoretical framework for the continuous assessment of the environmental impact of cement production.

3.2.1.1 Scope of the model: Functional Unit and System Boundaries

The functional unit adopted on a mass basis is the production of 1 metric ton of cement. The cradle-to-gate system boundary is used for this study. Only activities that occur before arriving at and within the cement plant are considered since performance and impacts after the cement plant are identical across product systems and irrelevant for impact comparison purposes.

Table 3. Parts of LCA and examples compiled from literature

	Lifecycle Stage	Cement	Cement	Clinker	Clinker	Concrete	Concrete
Goal and Scope Definition	**Functional Unit**	1 ton Portland cement	1-ton ordinary Portland cement and 1 ton of clinker	1 ton clinker	1 kg of clinker	Varied specific measure of concrete	1 cubic meter of concrete
	System Boundaries	Raw materials and fuels extraction, transportation, electricity usage, emissions	Life Cycle Inventory analysis	Cradle-to-gate LCA model. Clinker production in cement kiln excluding blending and grinding	Cradle-to-gate LCA for old and new cement production lines. Clinker production excluding blending and grinding	Modified cradle-to-gate. Comparison of traditional and 'green' concrete	Cradle-to-gate LCA of graphene production and use in concrete
	Country	Brazil	China	Switzerland	Spain	N/A	UK
Lifecycle Inventory (LCI)	**Inputs and outputs**	In - Sand, Limestone, Clinker, chemical additives, transportation. Out - NOx, CO2, HCl, HF, Hg, Pb, Cd, Ta, Dioxins	In - Limestone, sandstone, ferrous tailings and gypsums, energy from coal and electricity, admixtures (fly ash and furnace slag, fresh water. Out - GHG, primary	In - Alternative fuel and raw materials (tires, prepared industrial waste, dried sewage sludge, blast furnace slag). Out - Carbon, nitrogen, chloride, fluoride compounds,	In - Limestone, sand, iron ore, clay, electricity generation, heat. Out - CO2, NOx, SO2 Particulates	In - Minerals and fossil fuels, land use. Out - NOx, SOx, NH3, pesticides, heavy metals, CO2, hydrochlorofluorocarbons (HCFC), nuclides, polycyclic aromatic hydrocarbons (PAHs), volatile organic compounds, suspended particulate matter (SPM)	In - Portland cement, Ground Granulated Blast-furnace Slag, Limestone, Sand, Water, Superplasticizer, Graphene nanoplatelets Paste, Input Energy

			pollution, hazardous air pollutants, noise, heavy metal emissions	clinker, raw meal, cement kiln dust			
	Data Source	Plant, National statistics, Ecoinvent database	On site, 18 cement plants with 30 production lines from 2004 to 2007	On site, Ecoinvent database	On site plant data. SimaPro 7.2 software. Ecoinvent 3.0	LCA related journals	Commercial Companies and scientific literature. SimaPro software
Lifecycle Impact Assessment	**LCIA method**		ISO Environmental Management - Life Cycle Assessment	Cumulative Exergy Demand (CExD) [30], Eco-indicator	Cumulative Exergy Demand (CExD) [71]	IPCC 2007 Global Warming Potential (GWP) impact method	Impact 2002 + methodology [74]
	Impact Analyzed	Ozone depletion, photochemical oxidant formation, terrestrial acidification, freshwater and marine eutrophication, metal and fossil depletion	Freshwater consumption, noise emissions, heavy metal and hazardous pollution emissions, indirect consumptions of oil and coal	Gas emissions	Global warming, acidification, eutrophication, abiotic depletion, ozone layer depletion, freshwater aquatic ecotoxicity, photochemical oxidation	Acidification, eutrophication, ecotoxicity, climate change, ozone layer depletion, ionizing radiation, respiratory effects, carcinogenic	Carcinogens and non-carcinogens, respiratory inorganics, aquatic and terrestrial ecotoxicity, global warming, non-renewable energy and mineral extraction
	Reference	[60]	[61]	[71]	[59]	[72]	[73]

Figure 5 shows a representation of the system boundaries, system elements, and unit processes depicting the exchange of energy (E), particulate emissions (PE), gaseous emissions (GE), and heat (H) in the quarrying, crushing, grinding, dry mixing and blending, preheater, rotary kiln, clinker cooling, additives, and final grinding processes in cement production.

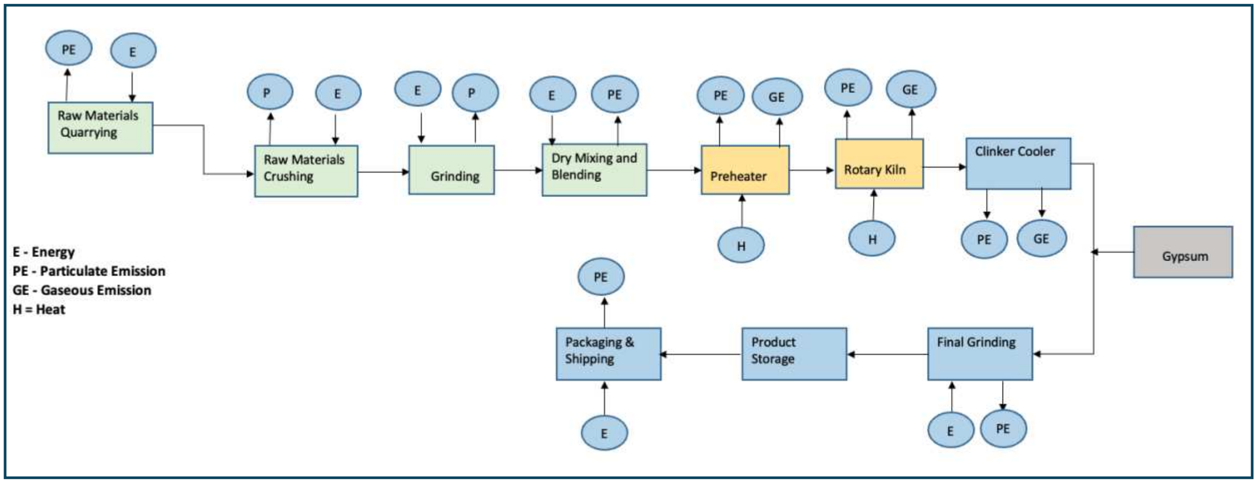

Figure 5. Graphical representation of the system boundaries, system elements, and unit processes

3.2.1.2 Life Cycle Inventory

This is the compilation of information on the inputs, outputs, waste generated, electricity, and thermal energy required to produce a functional unit of the product within the defined system boundary. The system boundary covers the following emission units listed by Lehigh Cement company in its operating permit as subject to Title V requirements and having applicable requirements [75]:

- Union Bridge Quarry Operations
- New Windsor Quarry Operations
- Raw Material Transport and Storage
- Raw Grinding
- Raw Meal – Kiln Feed
- Kiln and Clinker Cooler
- Coal Grinding Mill for Kiln

- Clinker Transport & Storage
- Clinker Finish Mills
- Cement Storage and Shipping with Bag Packing
- Dried Biosolids Related Processes
- Emergency Generator

The data switching for the scenarios for ordinary Portland cement, Portland-limestone cement, and the coal and alternative fuels are implemented using Excel's IF function on the cells of the inventory sheet highlighted in Figure 6 (*also see the 'INVENTORY' sheet of the quantitative data spreadsheet*). Relevant inventory data and impact assessment factors are sourced from data on power consumption and expert opinion at the Union Bridge plant of Lehigh Cement, documentation from the parent company Heidelberg Materials, calculation by coefficients and derivations from secondary data sources including libraries and databases from literature listed in notes, and amongst the sources listed in the 'SOURCE GUIDE' sheet of the quantitative datasheet in the supplementary material. Electricity from the national grid powers the crushing, grinding, conveying, and machine operation. Coal is used to generate the thermal energy required for the calcination process. This study also models production using thermal energy from the combustion of biosolids from treated sewage sludge from the Hampstead Waste Water Treatment Center in Carroll County, where the Lehigh Cement plant is situated. Dried biosolids are typically made from sewage sludge by maceration, pressurization, heating, decarboxylation reaction, and drying.

3.2.1.3 Life Cycle Impact Modeling

The attributional LCA approach described in [76] was adopted for this demonstration. This approach does not analyze the indirect consequences of the product's manufacture. It is generally restricted to using average impact data to allocate the environmental impacts of factors in the product's life cycle stages. The impact assessment factors are limited to the climate change impact category considered for this study (*see the quantitative data spreadsheet's 'Impact Assessment' sheet*). Carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) are the relevant gases related to the greenhouse effect. However, the relative contribution of CO_2 predominates, being between 98.8% and 100%, because it is emitted at much higher quantities than the other gases [77]. Therefore, emissions from methane and nitrous oxide were excluded from this LCI.

INVENTORY

Production Parameters

Parameter	Value	Unit	Notes
Annual production volume	2,000,000	t/year	total amount of final product manufactured by plant in 1 year
Operating days per year	337	day/year	days per year when plant is operating
Hours per day shift	10	hour/day	hours per day for shift
Shift positions in plant	3	position	total number of employees directly managing system at any given time
Conventional OPC market price	130	$/t	
Conventional OPC estimated emissions	817	kg CO_2-eq/t	kilograms of carbon dioxide equivalent from producing 1 ton of conventional product

Scenario Specifications

Scenario	1 or 0	On/Off	Notes
Scenario : Blended Cement	0	OFF	whether scenario 1 is turned on or not ("OFF" is the Ordinary Portland Cement without additional limestone)
Scenario: Alternative Fuel	0	OFF	whether scenario 2 is turned on or not ("OFF" is thermal energy using coal)

Material Parameters

Grinding Energy	Value	Unit	Notes
Electrical Energy Consumption CPC	79.58	kWh/t	Electrical energy consumption indicator - Conventional Portland Cement
Electrical Energy Consumption BC	75.6	kWh/t	Electrical energy consumption indicator - Blended Cement

Figure 6. Subsection of the Inventory sheet in the LCA

3.2.2 Techno-economic Assessment

The techno-economic assessment of the introduction of new technology or process is an important step when aiming to set a large-scale process, especially at the industrial level. To assess the economic viability of the change, TEA combines process modeling and engineering design with economic evaluation. TEA is apt for assessing decarbonization efforts from emission reduction methods in cement production.

System dynamics are considered suitable for handling the complexities of understanding the economic behavior of CCU technologies. Apart from investments and operational costs, other factors such as government policies, market conditions, material and information delays, and the feedback process in the supply chain impact the economic behavior of CCU technologies [78]. In the referenced article, the authors simulated indirect carbonation using different hydroxides as absorbent precursors to reduce CO_2 emissions in clinker production. They performed an analysis of the CO_2 captured using a system dynamics model.

They determined that CO_2 capture costs 65 to 140 USD/tCO_2 in the carbonation process and that a tax policy of 80 USD/tCO_2 or more will encourage the implementation of CO_2 capture.

In another assessment, the authors in [79] evaluated two Calcium Looping (CaL) processes for capturing CO_2 in cement plants – the first integrates the CaL in the cement kiln at the tail-end such that the placement of the CO_2 capture process is downstream in the clinker burning line and with fluidized bed reactors (CaO-rich sorbent). The other process integrates the CaL system with entrained flow reactors in which the carbonator is integrated with the preheater of the clinker burning line, treating only the flue gas from the rotary kiln. In their analysis, the authors determined that the tail-end and integrated CO_2 capture processes increased the cost of cement by 67% and, 74%, respectively, while the cost of CO_2 avoided was 52 EUR/tCO_2 and 58.6 EUR tCO_2, respectively. Example metrics of emissions captured and the related cost of leveraging oxy-combustion with calcium looping vary from 94% emissions captured at \$17/tCO_2 [80] to 60% emissions captured at \$40.6/tCO_2 [81].

The following are instrumental to reducing cement prices and CO_2 emissions: carbon tax, CO_2 capture efficiency, cost-effective and energy-efficient amine blend, energy penalty, and CO_2 sales price [82]. Even with the opportunities for CO_2 capture from the process emissions from calcination, which by concession from literature accounts for about 60% of cement production emissions, the cement industry is cautious about incorporating new technology that might affect clinker composition [83]. Therefore, alternative fuels with lower carbon footprints and technologies leading to lower energy requirements for heat generation for the kiln are also assessed for their economic viability at an industrial scale. The thermal energy (about 3.2 – 6.3 GJ per ton of clinker) required for cement production is provided by fossil fuels such as petroleum coke, natural gas, and coal. Alternative fuels considered in literature for cement production include tire-derived fuels, commercial and industrial wastes, sewage sludge, meat and bone meal produced from slaughterhouse residue, agricultural biomass, and spent pot linings [84].

In a study exploring the economic feasibility of a waste recovery system that captures radiation emitted from the surface of a rotary kiln [85], the authors determined that for markets with electricity costing as much as 0.1 USD/kWh, the method could yield as much as 5% return on investment (ROI) or net present value of $0.06 million. The authors evaluated the system by combining computational fluid dynamics simulations with process modeling, including mass, energy, and exergy balances

3.2.2.1 Techno-economic assessment method

Process costs for the estimated annual production of 2 million tons of cement at Lehigh Cement plant were considered in the techno-economic assessment. It evaluates the leading economic indicators, such as capital and cement production costs, including raw material, energy, property, plant, and equipment. Figure 3 is a summary table and pie chart for TEA indicators showing the distribution of overhead costs for the annual production of 2 million tons of ordinary Portland cement using coal for thermal energy. Equipment cost estimation was conservatively deduced from the acquisition cost of machines without accounting for freight, installation and taxes, and other capitalizable costs. Local pricing of production materials was used where available and national averages were adopted in other inputs. For instance, $0.1396/kWh, the average electricity price in Maryland [86], was adopted for electricity (see electricity cost sensitivity analysis in Section 3.3). In contrast, coal and dried biosolids' national average sales price was used.

INDICATORS

Indicator Summary

Process Costs	$/t	$/year	% of Total
Raw Materials	$ 44.14	$ 88,273,985	75.2%
Limestone, gypsum (incl. transport)	$ 38.87	$ 77,744,332	66.2%
Water	$ 5.26	$ 10,529,653	9.0%
Labor	$ 0.14	$ 271,595	0.2%
Direct labor	$ 0.08	$ 161,760	0.1%
Indirect labor	$ 0.01	$ 24,264	0.0%
Fringe	$ 0.04	$ 85,571	0.1%
Manufacturing Overhead	$ 14.42	$ 28,842,719	24.6%
Factory floor space	$ 0.00	$ 699	0.0%
Capital equipment	$ 0.16	$ 318,413	0.3%
Maintenance	$ 0.23	$ 462,834	0.4%
Insurance	$ 0.02	$ 30,856	0.0%
Utilities - electricity	$ 6.55	$ 13,101,918	11.2%
Heating Fuel	$ 7.46	$ 14,928,000	12.7%
Total Manufacturing Cost	$ 58.69	$ 117,388,299	100.0%

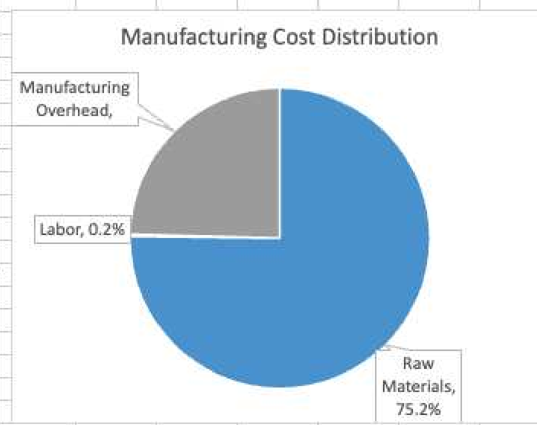

Figure 7. TEA Indicator estimates for annual production in the “OPC + Coal” scenario

Using actual vendor quotes is recommended for TEA accuracy. However, ballpark estimates for TEA parameters such as energy and raw material pricing are sufficient for hotspot analysis and for generating order-of-magnitude estimations [87]. It should be noted that this study is focused on demonstrating the implementation of the continuous assessment and improvement framework; practitioners that adopt this framework for business decisions are encouraged to use actual vendor-provided quotes for their implementation.

3.2.3 Continuous assessment and improvement deployment framework

Secured deployment of IoT-enabled solutions in the cement industry is drawing the attention of stakeholders because of the significant value in cost reduction, the increased efficiency, and the greater visibility that IoT devices can provide. IoT-related technologies have been explored in the following areas with trials in the cement industry:

- Secured deployment [88]
- Event tracking in supervisory control and data acquisition system [89]
- Fuzzy logic-based flame image processing for rotary kiln temperature control [90]
- IoT-regulated moisture sensor [91]
- Real-time carbon dioxide monitoring based on IoT cloud technologies – MQ135 carbon dioxide sensor, ESP8266 Wi-Fi module, Firebase cloud storage service, and Android application [92]

Figure 8 is a simplified depiction of the use of connected devices in the production of Portland cement through the dry method. Sensors measure raw materials from the quarry for quality, moisture, and pH value. Transportation of raw materials to the plant is tracked to measure cost and related emissions. Energy requirements of the crushers, fuel consumption, and CO_2 emission due to calcination at the kiln, moisture level, temperature, and coolers and grinders' energy consumption are all measured and then transmitted to cloud-based servers through a gateway device.

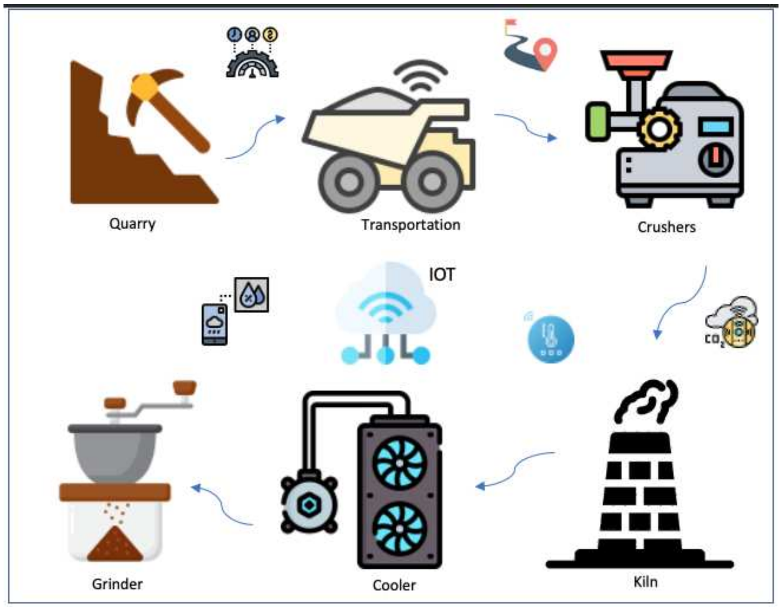

Figure 8. IoT-enabled cement production

CCUS pathways that need early-stage economic and environmental performance assessment template development were identified in the work in [55]. The authors synthesized existing guidelines and approaches into actual templates that can be adopted for early-stage LCA and TEA. These templates are editable with a programming language with Excel handling libraries to enable database integration, sensitivity and uncertainty analysis, and advanced visualizations for decision-making. Python programming language has several open-source libraries for Excel and can be adopted for integrating LCA and TEA templates [93]. In addition, the required scripting, macros, and user-defined functionalities are available in the free version of the open-source Python library Xlwings, which also supports Numpy arrays, Pandas Series, and DataFrames on Windows and macOS.

Figure 9 shows the schematic diagram of a continuous assessment and improvement framework for analyzing the environmental and economic impact of a cement production process improvement and feeding back data-informed decisions for managing the plant. In this framework, data is transmitted from the IoT-enabled cement plant to the cloud data platform via gateway devices that connect the disparate networks and translate communications from one protocol to another, thus allowing bidirectional data flow between the cloud and the IoT devices at the cement plant.

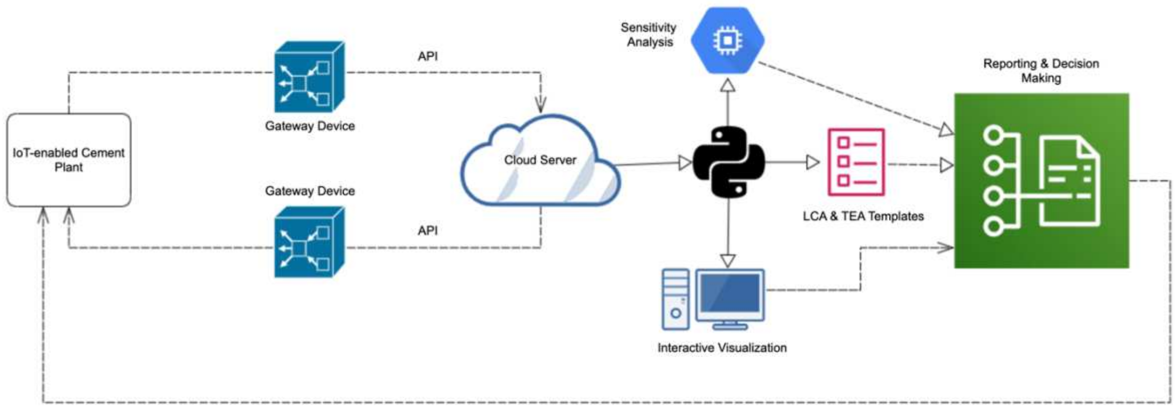

Figure 9. Continuous assessment and improvement framework

The cloud services include computing infrastructure, platforms, and cloud-native applications that facilitate data flow from IoT sensors to storage and data processing platform. Integration with a data warehouse is seamless with connectors and APIs, giving the platform access to life cycle inventory databases and other economic and operations data required for analysis in near real-time or batch processes. Relevant metrics measured from the cement plant are inserted into the LCA and TEA templates with Python installed on the platform. Similarly, the metrics are fed into sensitivity analysis and data visualization with Python. Economic and environmental improvement insights drawn out of these are used for business decisions, reporting for compliance, and as feedback for improving the production process.

3.3 LCA – TEA Results and Discussion

3.3.1 Impacts Analysis

Assessing the impact of the significant drivers of CO_2 emission for the four scenarios highlights the possible carbon reduction potentials of materials efficiencies from producing Portland-limestone cement to replace ordinary Portland cement and adopting dried biosolids as a thermal energy alternative to coal. Figure 10 shows the impact assessment results from the "OPC + Coal" scenario, estimating the contributions of the major drivers to climate change when using coal for thermal heating to manufacture ordinary Portland cement at the plant. Based on this impact assessment, calcination leads to more than half of process emissions (about 54%), with the emissions attributable to combustion comprising most of the remaining emissions burden (about 40%). The emission from the other drivers, such as electricity, water, and transportation, contribute an estimated 6% of process emissions.

The production of a ton of ordinary Portland cement with thermal energy from coal is estimated to result in a global warming potential (GWP) of 856 kg CO_2-eq. 100-year time horizon GWP, as provided by Intergovernmental Panel on Climate Change [94], gives a standard unit of measure of how much energy the emissions of a ton of a gas will absorb over some time relative to the emissions of a ton of carbon dioxide, the gas used as a reference.

The estimate of climate change contribution by drivers varies under different scenarios, such as the production of Portland-limestone cement and the use of dried biosolids. Table 4 summarizes the climate change driver contributions in these scenarios. The results indicate the potential of reducing greenhouse gas emissions from 856 kg CO_2-eq per ton of ordinary Portland cement using coal for heating, to 788 kg CO_2-eq per ton of Portland-limestone cement using dried biosolids for heating. This is an opportunity for a 7.9% reduction in CO_2 emission from material efficiency.

IMPACT ASSESSMENT

Impact Assessment Results Summary

Climate Change by Driver (kg CO_2-eq)	Per t	Per year	%
Calcination	465	930,160,000	54.3%
Combustion	339	678,400,000	39.6%
Transportation	3	5,870,880	0.3%
Water	34	68,057,512	4.0%
Electricity	15	30,628,932	1.8%
Ordinary Portland Cement Emissions	0	1,713,117,324	
Portland-limestone Cement Emissions			
Total Emissions Savings	55	111,149,551	
Thermal Heating with Coal			
Ordinary Portland Cement Emissions	856	1,712,648,313	
Blended Cement Emissions	801	1,601,498,762	
Total Emissions Savings	56	111,149,550	
Thermal Heating with Biomass Fuel			
Ordinary Portland Cement Emissions	844	1,688,376,313	
Blended Cement Emissions	788	1,576,468,762	

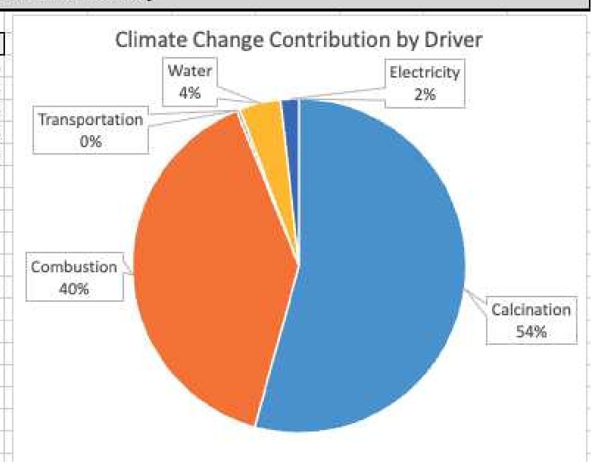

Figure 10. Summary and pie chart for LCA impact assessment

Table 4. Summary of climate change driver contributions for four raw material scenarios

#	Scenario	Calcination	Combustion	Others	GWP (kg CO2 eq)
1.	OPC + Coal	54.3%	39.6%	6.1%	856
2.	OPC + DBS	55.1%	38.7%	6.2%	844
3.	PLC + Coal	51.3%	42.4%	6.4%	801
4.	PLC + DBS	52.1%	41.1%	6.5%	788

OPC = Ordinary Portland Cement
DBS = Dried Biosolids
PLC = Portland-limestone Cement
GWP = Global Warming Potential
GWP 100 = 100-year time horizon GWP provided by the IPCC 2013 Fifth Assessment Report [94]

Portland-limestone blended cement, which has additional limestone used as an ingredient amounting to about 15% of the mass, has reduced calcination and fuel combustion CO_2 emissions when compared to ordinary Portland cement. The assessment indicates that the production of the blended cement has a 6.4% lower carbon footprint than the production of the ordinary Portland cement at the Lehigh Cement plant at Union Bridge, reducing emissions from 856 kg CO_2-eq/t to 801 kg CO_2-eq/t. Going by annual production of 2 million tons of cement, the switch to the Portland-limestone cement positions the plant to avoid approximately 123,000 tons of carbon dioxide emissions annually. This could be a cost more than $3million if there were a tax of $25/ton. In 2022 carbon tax rates in the United Kingdom was $24/ton and as high as $137/ton in Uruguay [95]. Using renewable energy sources for electricity to power the crushers and grinders would further reduce the climate change arising from process electricity use. However, we need to be circumspect when interpreting data for impact categories because emerging LCA impact categories and inventory items are still under development, can vary depending on the source of data and specific situations in the analysis, and can have high levels of uncertainty that preclude acceptance pending further development.

Using a continuous emission monitoring system (CEMS) is vital for emission data input in implementing the continuous assessment and improvement framework. CEMS is the equipment required to determine the gas concentration or emission rate. It is required for some United States Environmental Protection Agency regulations for continual compliance or to determine if emission standards are exceeded.

CEMS use pollutant analyzer measurements and a conversion equation, graph, or computer program to produce results in units of the applicable emission limitation or standard [96].

3.3.2. Economic Analysis

The economic analysis is premised on the annual production of 2 million tons of cement at Lehigh Cement's Union Bridge plant. Based on the indicator summary, the estimated optimal cost of producing a ton of ordinary Portland cement using coal is $58.69. However, producing similarly performant Portland-limestone cement using dried biosolids can reduce this cost by 10.87% to $52.31/ton (*see the 'Indicators' and 'Inventory' sheets of the quantitative data spreadsheet in supplementary material*).

The *sensitivity analysis* of the production volume of cement at the plant indicates that given the estimated data points, the cost-optimal production volume is 2.4 million tons at the cost of $58.6/ton. Figure 11 plots the manufacturing cost sensitivity of ordinary Portland cement to the production volume at the plant. The inflection point on the cost is at an annual production volume of 800,000 tons.

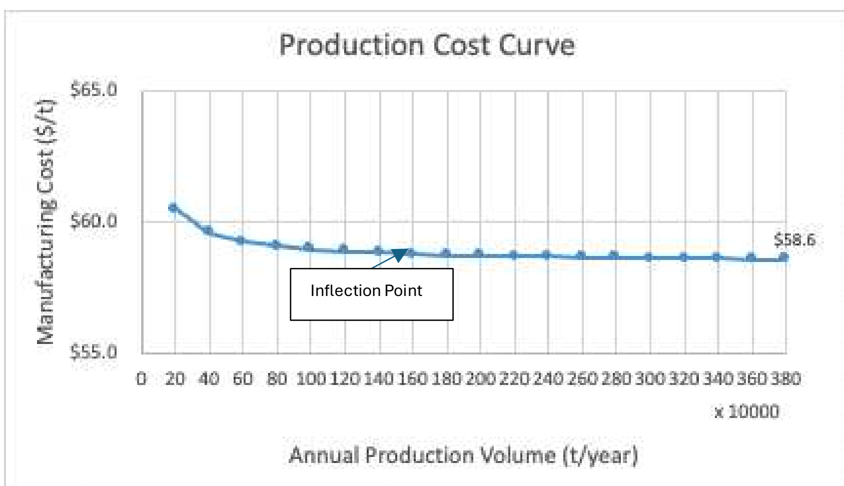

Figure 11. Cost sensitivity to production volumes

In addition, sensitivity analysis of the cost of electricity indicates that production cost increases by 12% to $65.77 when cost of electricity goes up from $0.15/kWh to $0.33/kWh. September 2021 average costs of electricity in US states ranged from $0.10 in Arkansas to $0.33 in Hawaii [97]. Figure 12 is a plot of manufacturing cost sensitivity to the cost of electricity. Distance from the quarry to the plant can also impact the cost of production due to the increase in transportation costs. However, the cost in this analysis is premised on the proximity of the New Windsor quarry to the cement plant. The crushed material from the quarry is transported to the cement plant via 4.5 miles-long overland conveyor.

The uncertainty analysis indicates that the number of personnel available on work shifts did not significantly affect the cost of production because plant personnel cost is only 0.2% of the cost of production. However, fluctuations in the cost of other raw materials can impact the cost of production

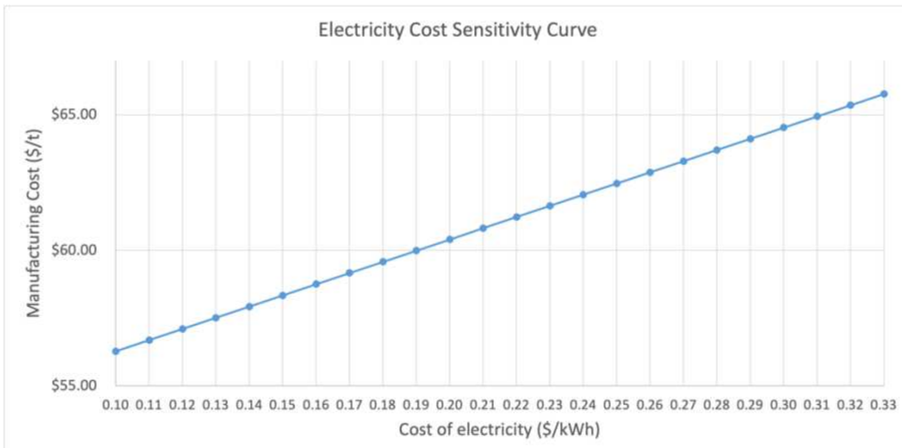

Figure 12. Production cost sensitivity to electricity cost

Figure 13 plots the cost sensitivities to production volumes for the four production scenarios highlighted in Table 4. It visually compares the cost sensitivity to production volume using the different production inputs in the four scenarios. The visualization was created using the subplot() function in Matplotlib that enables drawing multiple graphs in a single plot. Matplotlib is a comprehensive Python library for creating static, animated, and interactive visualizations [98].

The plots have a similar shape with declining cost/ton as production volume increases until the point of inflection when cost/ton remains stable despite further production increases. Notice, however, that production cost is lower in the scenarios where thermal heat is provided from the combustion of dried biosolids. The model uses fair market pricing for dried biosolids made from drying sewage sludge with a heating value of approximately 7,000 Btu/lb. The economic analysis can be expanded to include the capital investment required to dry the sewage sludge if it is within the boundary of the analysis for a production plant that produces its alternative fuel as part of the circular economic process.

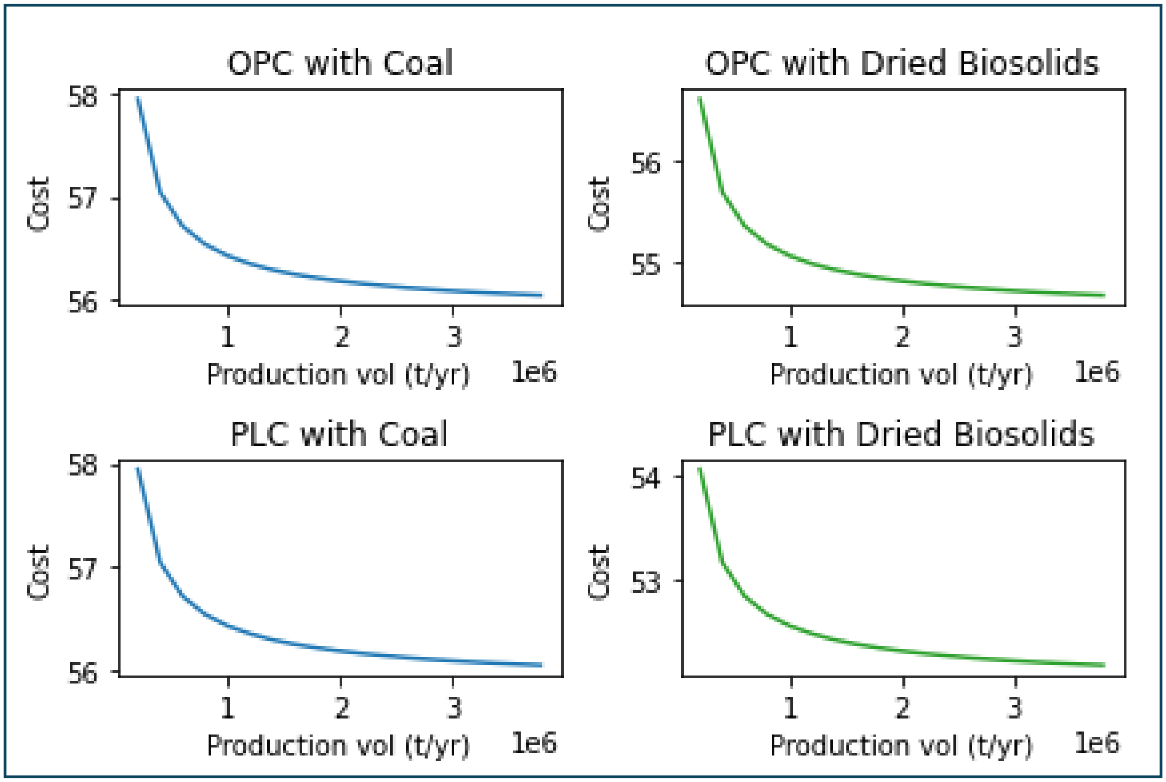

Figure 13. Plots of cost sensitivity to production volumes in four production scenarios

3.3.3. The Deployment Framework

This study contributes to developing practical approaches to integrating sustainability into cement production. It addresses integrating economic and environmental impact assessments into cement production operations. The framework can facilitate the dynamic implementation of sustainability innovations and the continuous measurement of their performance. Beyond mere rhetoric, cement manufacturers that have made a public commitment to fighting climate change can leverage this deployment framework in whole, or parts, to be on their way to meeting their emission reduction targets. This is demonstrated using production scenarios at a US cement plant.

The continuous assessment and improvement deployment framework enables dynamic management of production inputs to optimize the cost of production and reduce carbon emissions. The problem is expressed as a minimization of production cost by defining it as a linear function subject to linear constraints. The constraints considered include the demand for cement types, the cost, and availability of raw materials such as alternative fuels, emission compliance requirements, and the company's commitment to lower emissions. The computation is executed as a linear programming problem to find the feasible region and optimal solution. Data to define the linear constraints based on cost, availability, operational policies, and compliance are pulled from readings at the plant and supplied interactively by process managers. Complex computations and graphical representations of the information are enabled by leveraging appropriate libraries and APIs in the cloud platform. Insights thus generated aid decision-making and position the cement plant as a dynamic, innovative, and responsible business committed to its operations' sustainability and open to rapid testing and experimentation.

The framework has opportunities for further optimization. It can also be coupled with other business operation and reporting systems to source actual operations and financial metrics as input data and directly supply needed information to the other systems. Business uncertainties such as raw material price volatility can be quantified using Python libraries for Monte Carlo simulation.

Chapter 4 – Artificial Intelligence Applications in Electrical Energy Consumption Optimization

Despite its obvious purpose, research on the implementation of electrical energy–saving measures at the plant level has been surprisingly slow. Hence, this systematic literature review aims to articulate the following:

1. The research that has been done and the methods that have been investigated in the optimization of EEC in cement manufacturing.
2. The contributions of previous investigations to EEC optimization and the gaps that need to be addressed.
3. The application of AI, and other methods and approaches applied to EEC optimization in other power–consumption heavy industries.
4. The potential areas of future research in cement manufacturing EEC optimization, and the inherent opportunities to leverage AI applications.

At the nexus of sustainability and industrial development, cement manufacturing presents a unique challenge in curbing energy consumption without compromising the quality and quantity of production. This study contextualizes the significance of optimizing EEC, addressing the industry's demand and its implications for environmental sustainability. The rationale behind this study stems from the urgency to reduce the environmental impact of cement manufacturing while ensuring its operational efficiency [18, 20]. The electric power the cement plants consume is significant, and the generation of the electricity consumed contributes to the carbon footprint due to the indirect impact of the power plant which uses either fossil fuel or natural gas to generate electricity. There are research efforts on alternative ways to generate electricity; however, there seem not to be as many research efforts focused on optimizing electricity consumption in cement manufacturing. Analyzing and synthesizing the existing body of knowledge is

2. This chapter includes part of the publication: Oguntola, O., Boakye, K., & Simske, S. (2024). Towards Leveraging Artificial Intelligence for Sustainable Cement Manufacturing: A Systematic Review of AI Applications in Electrical Energy Consumption Optimization. Sustainability, 16(11), 4798. https://doi.org/10.3390/su16114798

pivotal to identifying gaps, novel advancements, and future directions for optimizing EEC in this vital industry. This study aims to critically examine and consolidate insights from a wide array of scholarly articles, industry reports, and research studies.

Discovering a dearth of research on the optimization of EEC in cement manufacturing, this literature review explores approaches adopted in other industries with high power demand. It further explores the relatively untapped potential for leveraging artificial intelligence to optimize EEC in cement manufacturing. Thus, it contributes to the evolving discourse on sustainable practices within cement manufacturing and endeavors to identify opportunities for innovation, foster informed decision–making, and propel the cement manufacturing industry toward a more energy–efficient and environmentally conscious future.

4.1 Literature Review Method

The systematic review process described in [99] was adopted for this study. The first stage of the process includes identifying a need for a review and developing a review protocol. In the second stage, we select the papers, assess their quality, and extract and synthesize data and relevant information. The final stage involves analyzing and interpreting the content, reporting the findings, and making recommendations for further research. The article selection process was streamlined into four steps: keyword selection, relevant database search, criteria–based shortlisting of articles, and selection of articles for in–depth review.

We selected search terms from the scoping study and discussions within the review team to conduct a comprehensive and unbiased search. The keywords and term adopted was “electric energy consumption optimization in cement manufacturing" to identify contributions related to electric power optimization, specifically in cement manufacturing. The keywords selected stem from the main concept of the area of study and it is intended to aid the identification and location of relevant literature and resources from various databases and search engines.

All contribution types, including articles, conference papers, and literature reviews published between 1993 and 2023, were considered, and relevant ones were included in the study. The search was conducted across Google Scholar, Scopus, IEEE EXplore, and PhilPapers databases. These databases contain scholarly resources relevant to the search topic

The most relevant 120 from a sample of peer–reviewed publications matched on Google Scholar (each with at least 100 citations) were assessed. Most of the matches came from a match on power optimization; however, most were not cement manufacturing applications. Other relevant articles were selected from Scopus, IEEE EXplore, and PhilPapers databases. The literature survey indicates that studies on power consumption optimization in cement manufacturing are limited in number and scope, and that this paper can contribute to a better understanding of strategies for optimizing EEC in cement manufacturing. The selection criteria are summarized in Table 5 below.

Table 5. Literature review selection criteria.

Items	**Criteria for selection**
Keywords/Term	"Electric energy consumption optimization in cement manufacturing"
Databases	Google Scholar, Scopus, IEEE Explore, and PhilPapers
Source	Article title; Abstract; Keywords
Time frame	1993 – 2023
Document typology	Article; Conference review; Literature Review; Conference paper

Research articles were identified and selected based on their focus and relevance to power optimization in cement manufacturing. Then, we did a backward–forward search by reviewing the references of the articles in our initial selection and identifying relevant articles that cited the ones in our initial sample [100]. After screening titles and abstracts, full–text articles were reviewed for eligibility, and 25 papers were finalized for detailed analysis. These papers' full texts were evaluated in detail to identify the main themes and perspectives. Figure 14 highlights the steps adopted for selecting the literature reviewed.

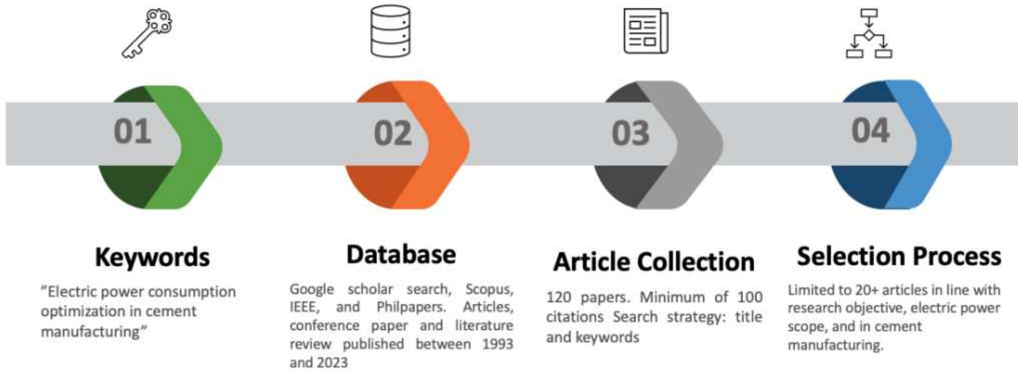

Figure 14. Literature selection

In comparison to applications in cement manufacturing found in literature, we reviewed the applications of AI to EEC optimization in manufacturing industries that have a heavy demand for electric power, including metals and mining, chemicals and petrochemicals, electronics and semiconductors, food and beverage processing, pulp and paper, automotive and transportation equipment, and textiles and apparel.

The quality assessments adopted include exploring and comparing different sources of knowledge for data quality, reviewing theoretical adequacy, and confirming that the claims made are generalizable logically and theoretically from the data [99]. Our analysis followed the descriptive design highlighted in the structuring content analysis approach of [101], which analyzes the texts to find the power optimization categories and register the occurrence of the categories. For instance, the adoption of power–efficient equipment occurred frequently in the literature, suggesting significant cumulative power–saving effects from implementing multiple strategies.

We organized the discussion on power–efficient equipment around processes in the different heavy power consumption subsystems of cement manufacturing. These include general electrical power management, gas handling and pneumatic systems, motors and transmissions, and comminution and separation. Other major categories in the literature include automation and process control along with adopting Industry 4.0 concepts. These categories formed the key themes around which we frame our findings in the following section.

4.2 Literature Review Results

The literature review findings will be presented and discussed in the following sub–paragraphs identifying opportunities for EEC in electric power management, gas handling and pneumatic systems, motors and transmissions, and comminution and separation. First, we provide a descriptive analysis of relevant literature. Subsequently, we describe energy–saving opportunities from the cumulative effect of adopting power–efficient equipment. Then, we highlight the opportunities within other categories, such as automation and process control, digitalization, and adoption of Industry 4.0 concepts. We also examine how other industries that have heavy demand for electrical energy implement EEC optimization by leveraging AI. The potential role of advanced analytics and AI in achieving electric power optimization in cement manufacturing specifically is further discussed, focusing on its potential to be leveraged for energy data analysis, predictive modeling, process optimization, and integration with energy management systems.

4.2.1 Descriptive Results

The research trend (Figure 15) indicates recent interest in electrical energy optimization in cement manufacturing. There is a recent increase in awareness of the importance of energy conservation and environmental protection. With EEC accounting for more than 60% of the total consumption and the higher cost of electricity linearly increasing the cost of production [18], energy conservation in cement manufacturing is key to the economical and sustainable production of cement. Optimizing electrical energy consumption in the production process can improve energy efficiency, reduce operational costs, and mitigate environmental impacts. It is worthy of note that all nine of the shortlisted publications that are focused on digitalization and the application of Industry 4.0 concepts were all published between 2018 and 2023, and involve the use of simulation, modeling, or analytics.

Table 6 groups the literature [102–123, 8] into the different electrical energy–saving categories elaborated in the papers. Many of the papers covered multiple categories, compared potential energy–saving opportunities, and aligned with the concept of accumulating power savings by adopting multiple power–saving methods.

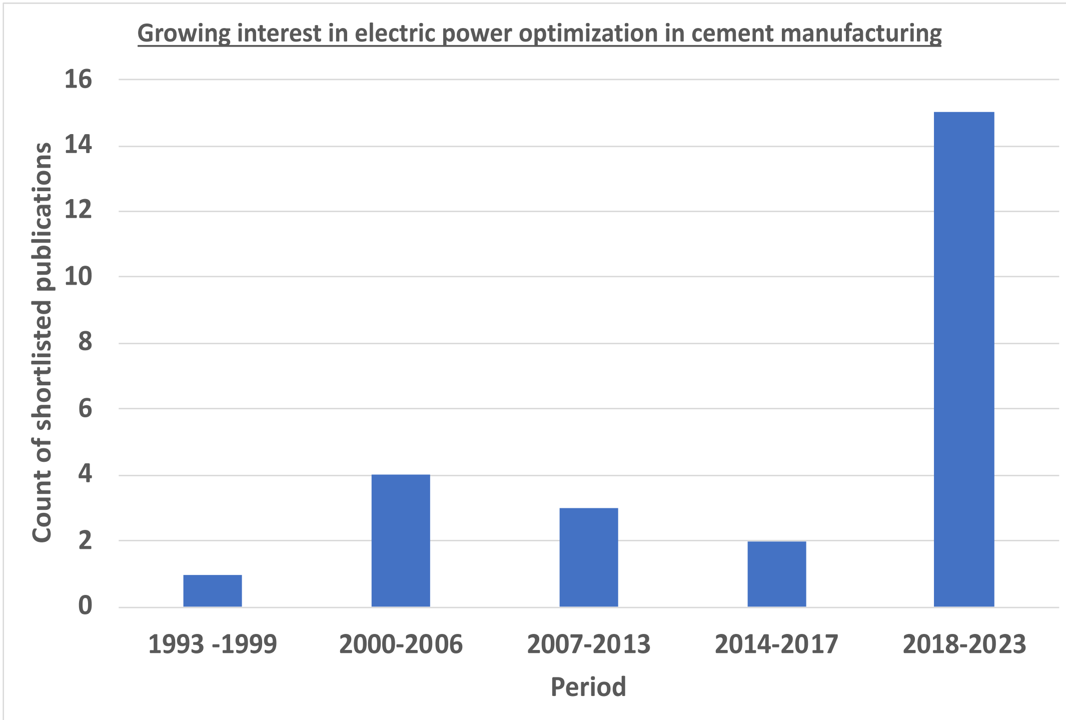

Figure 15. Distribution of relevant literature contributions

Table 6. Categories of electric energy saving opportunities in literature

Electricity Saving Category	Source Types	Number of Papers	Literature References
Energy efficient equipment and technologies	Conference proceedings, Journals	6	[102], [103], [104], [105], [106], [107]
Pyro–processing, grinding and milling opportunities	Journals	2	[108], [109]
Raw material, recycling, circular economy	Journals	2	[110], [111]
Waste heat recovery and power generation	Journals	3	[112], [113], [114]
Automation and process control	Journals	5	[106], [107], [111], [115], [116]
Digitalization (Industry 4.0)	Conference proceedings, Journals	8	[116], [117], [118], [119], [120], [121], [122], [8], [123]

4.2.2 Energy-saving Opportunities

The raw materials preparation process in cement manufacturing which includes quarrying, crushing, grinding and the blending of limestone with other materials, the calcination in the kiln, clinker cooling, and the final cement grinding are all electrical-energy intensive processes. Figure 16 is a schematic representation of the cement manufacturing process showing the electrical-energy intensive processes and emissions. The following subsections describe some of the energy–saving opportunities applicable to the cement production process.

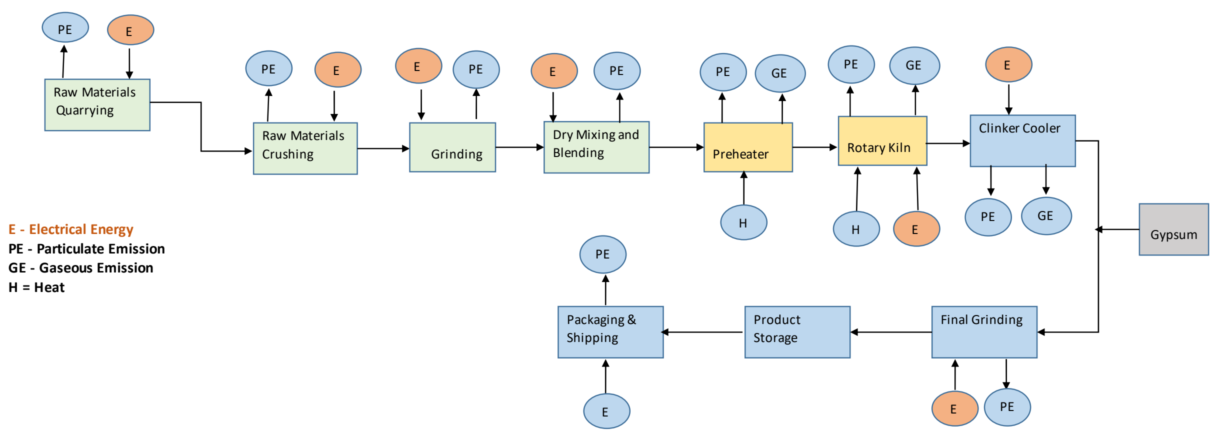

Figure 16. Schematic representation of a cement manufacturing process highlighting the electrical energy-intensive steps

4.2.2.1. Energy efficient equipment and technologies

Advocacy for adopting energy–efficient equipment was found to be common in literature within the period in consideration. As cement manufacturing equipment technology evolved, the advances were applied to curtail electricity costs by reducing specific power usage [102 –105]. Before the first period (1993–1999), there were improvements in fuel energy requirements, and the adoption of alternative fuels increased, while specific electrical energy consumption increased by as much as 40%. Many cement plants in Europe and North America at the time had higher electrical bills than fuel bills. The high bills drove innovations that created power reduction opportunities within electrical power management, gas handling and pneumatic systems, motors and transmissions, and comminution and separation [102].

With modern electrical power management technology, cement plants are digitalized, and computerized monitoring of motors and starters is implemented so that all the data collected can be analyzed to develop control strategies. These data–driven power management strategies include production planning to shift loads and maximize on–peak and off–peak demand power rates, preventing unnecessary equipment idling, and studying the causes of power variation.

Worrell et al., in their research [103], examined strategies for decreasing energy consumption and carbon dioxide emissions in US cement production by gathering data on the costs, energy conservation, and reductions in carbon dioxide emissions associated with various technologies and approaches. These methods were classified into two groups: existing measures widely adopted in cement plants globally and innovative measures that were either minimally implemented or on the brink of commercial viability. Using an energy conservation supply curve, the authors assessed the cost–effectiveness of the potential for improving energy efficiency. Energy conservation supply curves compare investments in energy conservation against investments in energy supply to take the least–cost approach to meeting energy needs. According to the findings, switching products to blended cement resulted in total fuel savings of 1.41 GJ/t of blended cement but an estimated increase in electricity consumption by 17kWh/t from grinding the blending materials. Estimated electricity savings from energy–efficient technologies for cement making in the US in 1994 ranged from 0.03 GJ/t from using high–efficiency roller mills to 0.07 GJ/t from adopting heat recovery for power generation. The International Energy Agency reported that from 2010 to 2020, the thermal energy intensity of clinker decreased by 0.2% annually [11]. However, it has since plateaued at around 3.6 GJ/t. This decline brought a rise in the sector's electricity intensity, estimated at 100kWh/t cement since 2022. This indicates that some of the advancements in thermal energy efficiency in cement manufacturing resulted in increased electrical energy consumption within the sector.

Common to many of the papers reviewed is an advocacy for the adoption of methods that have the potential to save energy. Al–Mansour et al. [104] submitted that prompt activation of savings opportunities yields economic advantages and reduces both direct and indirect greenhouse gas emissions. The analysis of Slovenia from 1997 to 2020 illustrated that promptly implementing energy efficiency measures in the industrial sector is economically justified. Using analytical methods with a 'least cost' economics analysis approach, the authors opined that enhancements to internal industrial conversion systems, such as the co–generation of electricity and heat, contribute significantly to overall efficiency improvements. The 'least cost' method identifies the scope for cost–effective energy savings as a function of energy cost and investment criteria.

The report in [105] is a guide for energy and plant managers that covers more than forty energy–efficient technologies implemented in cement plants worldwide. It assesses the technologies' effectiveness in terms of energy and carbon dioxide savings, investment costs, and operation and maintenance expenses. It recommends a corporate–wide energy management program that advocates for changes in staff behavior and attitude, energy efficiency training programs, and a formal management structure for managing energy.

Energy–efficient technologies are often combined with process controls to reduce energy consumption and carbon emissions [106–107]. Madlool et al. [106] surveyed energy efficiency measures for raw materials preparation, clinker production, products and feedstock changes, and finish grinding. Table 7 summarizes the estimated electrical energy savings and emission reductions reported in the paper from energy efficiency measures at each stage of the cement manufacturing process. The study indicated that as of 2013, the largest recorded amount of electrical energy savings from the adoption of energy efficiency methods was 35kW h/t.

One factor that should be addressed when implementing efficiency improvements in the manufacturing process is the economic viability of the proposed improvements. In a study that presented energy–saving measures with varying degrees of complexity and investment requirements, cost savings achieved surpassed the investment cost of implementing actions by 0.9 million USD [107].

Table 7. Aggregation of estimated electrical energy savings and emission reductions reported by Madlool et al. [106]

Energy–efficiency measures	**Electrical Energy Savings (kW h/t, *GJ/t)**	**CO_2 Emission Reduction (kg/t)**
Efficient transport systems for raw materials preparation – pneumatic systems, mechanical conveyors, pipe conveyors	2 – 3.4	0.41 – 3.22
Raw meal homogenizing systems	1 – 4.3	0.26 – 2.73
Raw meal process control for vertical mills	1.02 – 1.7*	0.16 – 1.45
Use of roller mills	6 – 11.9	1.24 – 10.45
High–efficiency classifiers/separators	3.18 – 6.3	0.51 – 5.23
Energy management and process control systems for clinker making in kilns	2.35 – 5	2.48 – 16.61
Adjustable speed drive for kiln fan for clinker making in all kilns	4.95 – 6.1	1.4 – 6.27
Low–temperature heat recovery for power generation for clinker making in rotary kilns	20 – 35	4.6 – 31.66
High–temperature heat recovery for power generation for clinker making in rotary kilns	17.84 – 22	3.68 – 9.25
Low–pressure drop cyclones for suspension preheaters for clinker making in rotary kilns	0.66 – 4.4	0.16 – 2.67
Efficient kiln drives for clinker making in rotary kilns	0.45 – 3.9	0.16 – 0.9
Process control and management in grinding mills for finish grinding	1 – 4.2	0.9 – 4.11
Vertical rollers mill for finish grinding	10 – 25.93	8.82 – 26.66
High–pressure (hydraulic) roller presses for finish grinding	8 – 28	1.28 – 25.09
High–efficiency classifiers for finish grinding	1.9 – 7	0.4 – 2.07
Improved grinding media (for ball mills)	1.8 – 6.1	0.29 – 6.27
High–efficiency motors and drives	0 – 25	0 – 47
Adjustable or variable speed drives	0.08 – 9.15	1 – 9.41
Changing product and feedstock – blended cements		0.3 – 213.54
Use of waste–derived fuels		12 – 76.31
Changing product and feedstock – Limestone Portland cement	2.8 – 3.3	8.4 – 29.86

Implementing energy–efficient technologies led to a 10.45% reduction in electrical energy consumption between 2008 and 2010. Notably, the improvements in process control techniques introduced during the same period resulted in substantial energy savings, with a 22.6% improvement in specific electrical energy consumption.

The authors employed the cumulative sum of differences technique to evaluate the effectiveness of the implemented actions. Therefore, with this know–how, there is an argument to be made that the cement manufacturing industry will gain much in cost savings and reduce CO_2 indirect impact by looking at innovative ways to optimize electrical usage at the plant level.

The articles reviewed indicate that the adoption of energy-efficient equipment and technologies in cement manufacturing has the potential to reduce energy consumption, electricity costs, and carbon dioxide emissions. Also, it is important to ascertain the economic viability of efficiency improvements to ensure manufacturer's motivation to implement.

4.2.2.2 Pyro–processing, grinding and milling opportunities

Quarry crushing is the start of the preparation of the raw material needed for the manufacturing of cement. The crushing process which also consists of conveying blasted limestone material consumes electricity because of motor drives. The process accounts for a small percentage compared to the other processes. Raw material milling, which follows the quarry crushing to reduce the material to fines for cement manufacturing also consumes electricity because of the raw mill motor drive. Compared to the other processes, however, it is a small percentage. Pyroprocessing is a term used to describe the high-temperature thermal treatments that occur during cement manufacturing. The processes involve using intense heat to transform grounded raw materials into clinker, the primary component of cement. Considerable electrical energy is required to power the kiln drive system motors and gears, the preheater and pre-calciner systems fans and blowers, the clinker cooler system, and the numerous auxiliary equipment such as air compressors, pumps, lighting, and control systems. In a study, raw material processing, clinker burning, and clinker grinding accounted for 28%, 25%, and 32% of electrical energy consumption, respectively [107]. Demandside energy management measures can provide immediate and short-term improvements in energy efficiency. Examples of these measures include leveraging free and low-cost options such as motor, compressed air, and process heater optimization software tools, energy management training programs, and energy assessments and audits.

After the clinker has been cooled, it's stored in clinker domes or silos, in storage bins or heaps outside. It is conveyed to storage, and to the finish mill for further grinding, using belt conveyors, deep bucket conveyors or bucket elevators, which can also dump it directly into silos or bins for shipment. To produce powdery cement, the nodules are ground to a fine powdery consistency. Approximately 3-5 per cent gypsum is added to regulate the setting properties of the cement. These powders, clinker and gypsum, are ground in ball mills or a combination of ball mills and roller presses, in roller mills, or roller presses Vertical roller mills are technically feasible, but they have yet to be widely accepted in the US. Coarse material generated by all these systems is screened and returned to the mill for further grinding to ensure a uniform surface area of the final product. The electrical power required to grind the raw material depends on the required surface area of the final product, the additives used, the hardness of the materials used (principally the limestone, clinker, pozzolana extenders), and the desired fineness of the cement [105].

In a study of a methodology to shift electricity consumption to economical off-peak periods, various physical components such as the raw mill, the kiln, crushers, cement mill, and auxiliary equipment were integrated into a simulation model to accurately predict their influence on production and cost [108]. Utlu et al. [109] examined pyroprocessing energy-saving opportunities in a Turkish cement plant using actual operational data. They proposed a tool for the analysis of energy and exergy utilization, the development of energy policies, and the provision of energy conservation measures. However, delivering energy-efficient technologies to consumers effectively is a challenge.

The pyroprocessing, grinding, and milling processes involved in cement manufacturing are energy-intensive due to the significant electrical energy consumed by the equipment such as motors, fans, mills, and conveyors. Some of the potential energy management measures recommended in articles include the use of optimization software, energy audits, shifting electricity consumption to off-peak periods, and the analysis of energy and exergy utilization data for the development of conservation measures.

4.2.2.3 Raw material, recycling, circular economy

More recent research efforts indicate that value can be derived from adopting recycling and the circular economy concept. The findings in [110] provide an estimate that recycled cement production using cement paste from concrete waste consumes 30% less energy than clinker production. The electrical energy consumption for an industrial setup is estimated by extrapolating laboratory results through simulations and analogies. The energy requirement is approximately one-third lower than conventional methods, as the concrete waste is already pre-crushed, thus reducing the need for extensive crushing to obtain fine aggregates. Additionally, the weaker nature of concrete waste compared to natural rock further contributes to the lower energy demand. However, compared to clinker, using concrete waste as a substitute has limitations that necessitate further investigation to comprehend the differences fully. While concrete waste exhibits lower reactivity and potentially lower strength characteristics, it has demonstrated acceptable results when used to replace up to 40% of Portland cement. Ambient air temperature and moisture content of the raw material also affect the performance of the raw mill and, in effect, the energy consumption. First and second law efficiencies of raw mill increase as ambient temperature increases and the moisture content of the raw materials decreases [111].

In summary, research suggests cement production from recycled concrete waste has the potential to reduce energy consumption when compared to conventional clinker production, however its possible limitations in strength and reactivity are worthy of further investigation.

4.2.2.4. Waste heat recovery and electric power generation

Researchers have explored waste heat recovery to generate power for cement manufacturing, as the process is energy-intensive and generates significant amounts of waste heat [112-114]. Mirhosseini et al. [114] confirm the feasibility and economic viability of generating electricity using thermoelectric generators (TEG) at the cement rotary kiln. The researchers propose installing a metallic frame acting as an absorber around the cement kiln, maintaining a specific gap from the kiln surface. This configuration serves two purposes: firstly, it facilitates heat recovery by thermoelectric generators, and secondly, it prevents the kiln from experiencing excessive temperature rise and additional weight. The study presents an optimal TEG system design that maximizes power generation by dividing the arc-shaped absorber into ten distinct sections. For each section, the study calculates the optimal design parameters for the TEG and corresponding heat sink, ensuring efficient heat transfer and electricity production.

Sanaye et al. [112] highlighted procedures for the modeling and optimum design of waste heat recovery and power generation systems. The modeling covered energy, exergy, economic, and environmental aspects. They reported on two parallel lines of cement production that were new and specific to the cement plant studied and leveraged a genetic algorithm for multi-objective optimization. The study's Organic Rankine cycle results showed that using water as a working fluid provided 9.14MW power output with an exergy destruction ratio of 47.9%. In contrast, using toluene as a working fluid provided a 6.56MW power output with an exergy destruction ratio of 53.5%.

Sani et al. implemented waste heat recovery by installing an air-quenching chamber at the clinker cooler's output and incorporating suspension preheater boilers in the preheating stage [113]. A genetic algorithm was employed to determine the optimal energy and exergy performance evaluation parameters, considering three different working fluids: water, refrigerant R123, and refrigerant R245fa. By optimizing the use of refrigerant R123, the power generation capacity increased significantly from 5MW to 9MW, whereas utilizing water as the working fluid only resulted in a modest increase from 4.8MW to 5MW. Furthermore, the analysis revealed that the refrigerant R123 exhibited a 4.1% decrease in total exergy loss, indicating its suitability as an efficient working fluid for cement plants' waste heat recovery cycle.

In summary, the feasibility and optimal design of waste recovery systems for generating electricity in cement manufacturing has been investigated by researchers. The approaches they have proposed include using TEG around the rotary kiln, incorporating air-quenching chamber at the clinker cooler’s output, and suspension preheater boilers in the pre-heating stage.

4.2.2.5 Automation and Process Control

Automation and advanced process control systems are critical for optimizing electrical energy usage in cement manufacturing. The cement production process is highly energy-intensive, with massive equipment consuming vast amounts of electricity. About two-thirds of the total electrical energy is used to reduce the particle size of raw materials and clinker. Practical methods to optimize the efficiency of the cement ball mill (CBM) were explored in a study of its energy and exergy in a new-generation cement plant [115]. The electrical energy consumption of the CBM unit was initially specified at 37.9 kWh/t. The study investigated the impact of factors such as ball charge pattern, cement fineness, and the addition of limestone and pozzolan on the performance of the CBM unit and the quality of the produced cement. By modifying the ball charge pattern, the first and second law efficiencies of the CBM increased to 81.8% and 20.6%, respectively, while the electrical energy consumption of the CBM unit decreased to 36.5 kWh/t. Furthermore, the results demonstrated that as the cement fineness decreased from 3250 cm2/g to 2820 cm2/g, the cement production rate increased from 185 t/h to 224 t/h, and the electrical energy consumption decreased from 41.1 kWh/t to 33.1 kWh/t. However, reducing the cement fineness affected the cement compressive strength (at 3, 7, and 28 days), which decreased while the cement setting time (initial and final) increased.

Gangwar et al. [116] developed a simulation-optimization method for scheduling energy-intensive industries under the uncertainty of the spot electricity market. This method, which can be adopted by the cement manufacturing industry for optimizing electricity costs, uses a Monte-Carlo scenario generator to generate future electricity prices and calculates the potential outputs for each of the plausible forecasted electricity price scenarios independently. Overall, the model identified the most profitable ways to operate an air separation plant in Spain under the uncertainty of electricity prices in the future.

By implementing automated control systems, parameters like equipment speeds, temperatures, and material flow rates can be dynamically adjusted based on real-time feedback to operate at peak efficiency. This prevents inefficient manual operation that wastes energy. Additionally, machine learning and artificial intelligence capabilities can be integrated to predict ideal operating setpoints and detect anomalies that increase energy drain. Automated monitoring also enables predictive maintenance, reducing unplanned outages and optimizing planned downtime for maintenance - avoiding wasteful energy consumption from faulty equipment. With rising energy costs and pressures to decarbonize, investing in automation and process control yields compounding paybacks through electrical energy savings while enhancing product quality, throughput, and environmental sustainability of cement production.

4.2.2.6. Digitalization

Potential benefits of digitalizing cement manufacturing include energy optimization, process automation and control, predictive maintenance, supply chain optimization, remote monitoring and control, product quality control, and data-driven decision-making. While digitalization requires upfront investments in technologies, systems, and skills, the potential benefits from efficiency improvements can result in significant cost savings, improved quality, and enhanced sustainability. Another potential benefit of digitalization is the standardization of data which allows the exchange, comparison, and integration of content between different parties in the industry. These provide valuable opportunities for cement manufacturers to remain competitive and adaptable to changing market demands.

Several research findings confirm the potential value of digitalization, subsequent data collection, and application of advanced analytics to the cement manufacturing process. In one instance, implementing model predictive control (MPC) technologies drove power consumption reductions ranging from 3% to 8%, simultaneously enabling increased production output and reduced fuel consumption rates [117]. In this study, two cement-related industrial MPC applications were presented – a cement raw-mix blending application and a cement mill grinding MPC application. A linear model predictive control algorithm with soft constraints was applied. By leveraging predictive modeling and optimization algorithms, MPC technologies can optimize various process parameters, improving electrical energy efficiency, and higher throughput, contributing to cost savings and sustainability goals.

Tong et al. [118] introduced the digitization work of a smart cement plant in China, which implemented intelligent factory technology using special integrated robots, software-as-a-service-based cement process digital applicant, artificial intelligence (XGBoost classifier), and advanced process control. Introducing these technologies gave potential energy savings ranging from 2% to 5% from improved process control. The primary production process in cement manufacturing is continuous, making process operation optimization or real-time optimization a crucial aspect. In their paper, Zhu et al. [119] presented a real-time optimization method based on system identification, which is particularly well-suited for energy and utility systems in cement plants. The proposed approach does not require rigorous mathematical models or specialized performance tests, making it a cost-effective solution. By leveraging system identification techniques, this method can optimize processes without complex modeling or extensive testing, thereby providing an efficient and economical way to enhance energy and utility systems in cement production.

In another study that shows the role that simulations and modeling can play in improving production, simulations and modeling studies were conducted to evaluate modifications to the existing cement grinding circuit flowsheet [120]. The proposed modifications involved redirecting the mill filter stream to the final product silo instead of sending it to the classifier feed. The simulations indicated that this modification would lead to a 4.45% increase in production rate, resulting in corresponding energy savings of 4.26%. This optimization approach not only improved energy efficiency but also enhanced the quality of the end product. Extensive investigations, laboratory validations, and post-production surveys were undertaken to validate the effectiveness of the modifications and ensure that product quality was not compromised. The results confirmed that the proposed changes did not adversely impact the quality of the cement product while delivering the anticipated benefits of increased production capacity and energy savings. Similarly, in another study, the specific electricity consumption of the raw mill workshop of a cement plant in Morocco was optimized while ensuring mill stability and quality control [122]. A multilinear regression model was used to test the effect of the independent variables mill throughput, hydraulic pressure, and mill outlet temperature against target variables of mill-specific electricity consumption and mill vibration.

Ye et al. [122] focused their study on modeling the primary energy-consuming equipment in cement manufacturing plants by utilizing industrial load characteristics and implementing a Markov process model. Subsequently, they used reinforcement learning algorithms to design demand response scheduling methods tailored for industrial applications. By combining the equipment modeling approach with advanced machine learning techniques, the study demonstrated intelligent energy management strategies that can optimize electrical energy consumption and enable demand response capabilities in energy-intensive cement manufacturing facilities. Artificial neural networks and genetic algorithms have also been applied to reduce the cost of electricity by optimizing different variables in the production process and regulated electricity market costs [123].

The best way for the cement industry to confront the challenges facing it and improve operational excellence is to embrace technological advances and innovations [8, 124]. The cement industry's major challenges include cost reduction, environmental protection, and energy/capital efficiency. Technological advances under the "Industrial Internet of Things" paradigm can be leveraged to address these challenges. These include process automation, engineering software, data collection/analysis platforms, secure data transportation, and storage solutions that provide real-time information for informed decision-making, help improve asset utilization and optimize relationships with customers and suppliers.

4.2.3. Leveraging AI for EEC optimization in other manufacturing industries

Research efforts have been directed at reducing electrical energy consumption in other manufacturing industries whose operations have a high demand for electrical energy, but this is lacking in the cement manufacturing industry. There is evidence in the literature that AI can improve energy efficiency by increasing technological efficiency [125-127]. For instance, in the metals and mining industry, the furnaces, electrolytic processes, and other energy-intensive operations required for smelting and refining metals like steel, copper, and aluminum consume considerable amounts of electrical energy. Artificial intelligence solutions were leveraged in an initiative that helped a steel manufacturer drive higher profit margins while meeting quality and quantity demand at reduced energy consumption levels. Pattern recognition and predictive modeling was applied to signals from sensors embedded in the mill to predict demand flow, asset flow, wear rates, and high-expense consumables used in production [128].

The production of various chemicals, plastics, and petrochemicals uses electric motors, pumps, fans and blowers, compressors, and compressed air systems. Motor systems use about 57% of the total electricity used in the chemical industry. 26% of the electricity is used by pumps, 23.6% is used in material processing, 27.7% by compressed air systems, 11.9% by fans, and 7.7% by refrigeration systems. Researchers have developed and tested a method that leverages descriptive analytics and neural network modeling to optimize the use of energy resources in chemical production [129]. Similarly, data analytics has been applied to optimize EEC in smart food processing achieving a 12% reduction in energy consumption and CO_2 emissions [130]. Optimization algorithms, mixed data sampling regression, and genetic algorithms have been used to reduce the electrical energy consumed in mechanical pulp production in the papermaking industry [131]. It is essential that the cement industry explore this novel idea to optimize its electrical consumption. No literature work was found during this work which shows that AI has been adopted by the cement industry to help optimize electrical consumption as other industries have done.

4.3 EEC Optimization Discussion

Infrastructural changes required at the cement plant to implement energy optimization often require significant capital investments [8]. Replacing aging equipment with more modern energy-efficient equipment and technologies often requires significant financial and human capital. Cement quality requirements are a constraint to swapping out or recycling raw materials. The adoption of automation and process control in cement manufacturing is getting attention. However, the fully autonomous cement plant is still a distant reality [132]. With innovation in sensors, interconnection of machines, automation devices, techniques based on IIoT, and advancement in cloud data storage and computing, large volumes of data on the operations of the cement plant can be collected. Even a staged implementation of digitalization in cement manufacturing can yield immediate, cost-effective results by applying advanced analytics to the data to generate transformative insights.

Table 8 is a synthesis of analytics methods applied in the literature for power optimization in cement manufacturing. The methods involve modeling and/or simulation of the electrical energy-intensive cement manufacturing process and applying a statistical method, an algorithm, or an optimization method to the model. Researchers have explored model predictive control applications [117], intelligent factory technology applications [118], real-time optimization [119], multilinear regression model [121], and reinforcement learning [122].

Energy data can be analyzed to uncover opportunities to reduce EEC. Cement plants generate massive amounts of data from various sources, including energy meters, process sensors, and control systems. Advanced analytics techniques can be employed to analyze this data and uncover patterns, trends, and insights related to energy consumption. This analysis can help identify energy hotspots, inefficiencies, and opportunities for optimization. By leveraging historical data and machine learning algorithms, predictive models can be developed to forecast energy demand, production rates, and equipment performance. These models can assist in optimizing energy usage by anticipating fluctuations in demand and adjusting operations accordingly, minimizing energy waste and peak loads. The output of the models can be incorporated into energy management systems that monitor and control energy consumption across the plant.

The use of digital twins and simulation in manufacturing is gaining attention. A high-fidelity digital twin of the cement grinding circuit can be developed using physics-based models and machine learning. Simulations can then be performed to test strategies for energy optimization before implementing them in the actual plant. Digital twins can also be used for virtual commissioning and operator training to improve human-process interaction efficiency.

The applications of AI to process optimization should be explored further for electric energy-saving opportunities in cement manufacturing. Advanced analytics can be used to optimize various processes within the cement plant, such as raw material grinding, clinker production, and cement grinding. By analyzing data from sensors and meters across the grinding circuit (mill, separators, fans, conveyors), we can determine the optimal setpoints and operating parameters (mill speed, feed rate, airflow) that minimize specific energy consumption while maintaining product quality.

Table 8. Analytics methods applied to power optimization in cement manufacturing

Literature and Country	**Themes**	**Analytical method**	**Insights**
Worrell, Martin, N., & Price, L. (2000) [103]. United States	Energy-efficient technologies	Energy conservation supply curve	Demonstrated that utilizing blended cement is a crucial and economical approach for enhancing energy efficiency and reducing carbon dioxide emissions in the US cement sector
Al-Mansour et al. (2003) [104] Slovenia	Energy-efficient technologies	Analytical methods with a 'least cost' economics analysis approach	The 'least cost' method identifies the scope for cost-effective energy savings as a function of fuel prices and investment criteria. Prompt activation of savings opportunities yields economic advantages and reduces direct and indirect greenhouse gas emissions. Enhancements to internal industrial conversion systems, particularly cogeneration of electricity and heat, contribute significantly to overall efficiency improvements.
Afkhami et al. (2015) [107]. United States	Process control and energy-efficient technologies	Cumulative sum of differences technique	Process control improvements resulted in 22.6% improvements in electrical energy consumption.
Sanaye et al. (2020) [112]. Iran	Waste heat recovery and power generation	Genetic algorithm for multi-objective optimization	Results for the study's Rankine (Organic Rankine) cycle showed that using water (toluene) as a working fluid provided 9.14 (6.56) MW power output with an exergy destruction ratio of 47.9% (53.5%).
Sani et al. (2020) [113].	Waste heat recovery and	Genetic algorithm to determine optimal parameters for	Optimizing fluid R123 increased power generation from 5MW to 9MW, while water only increased from 4.8MW to 5MW. R123 fluid also

Iran	power generation	energy and exergy performance evaluation	showed a 4.1% decrease in total exergy loss, indicating that it's suitable for the cycle.
Gangwar et al. (2023) [116]. Spain	Automation and process control, digitalization (modeling, industry 4.0, analytics)	Monte-Carlo scenario generator (MCSG), ARIMA (Autoregressive integrated moving averages)	Simulation-optimization method for scheduling energy-intensive industries under the uncertainty of the spot electricity market
Zhang et al. (2021) [117]. Turkey	Digitalization (control and optimization)	Linear model predictive control (LMPC) algorithm	Demonstrates that model predictive control (MPC) technologies can reduce power consumption by 3-8% while also increasing production and reducing fuel consumption.
Tong et al. (2023) [118]. China	Digitalization, Industry 4.0 concepts	SAAS-based cement process digital applicant, Artificial Intelligence, and Advanced Process Control (APC)	2 -5% potential energy savings from improved process control.
Zhu et al. (2022) [119]	Digitalization (modeling, industry 4.0, analytics)	Real-time optimization	A real-time optimization method based on system identification is especially suitable for energy and utility systems.
Altun, O. (2018). [120]	Digitalization (modeling, industry 4.0, analytics)	Simulation and modeling	This optimizes the energy efficiency and the quality of the end-product by modeling and modifying the existing flowsheet of the cement grinding circuit.
Belmajdoub, F., & Abderafi, S.	Digitalization (modeling,	Multilinear regression model	Optimization of specific electricity consumption

(2018) [121]. Morocco	industry 4.0, analytics)		
Ye et al. (2023) [122]. China	Digitalization (modeling, industry 4.0, analytics)	Markov process model and reinforcement learning	Design of industrial demand response scheduling methods using reinforcement learning algorithm

The production line of modern cement plants can be partitioned into these four sub-processes: crushing, kiln feed preparation, clinker production, and finish grinding. The cement manufacturing process heavily relies on electricity for various operations, such as crushing and grinding the raw materials, transporting substantial volumes of gases and materials throughout the facility, and grinding the final cement product. The electricity consumption of a grinding workshop is typically modeled as a function of the power demand of the equipment and the throughput of the material in the mill feed [121]. The objective is to optimize specific electricity consumption while keeping the mill operation stable and the product quality and production quantity according to plan. Effectively reducing electricity consumption reduces the carbon footprint due to the indirect impact of the electricity generating power plants which use either fossil fuel or natural gas. At a high level, the design of the optimization experiment will include the following:

- Identifying and modeling of the electrical energy-intensive components of the production process [133].
- Data measurement and collection of mill-controlled and manipulated parameters such as crushers, conveyors, mill motor and fan power, vibration, bed material height, residue fineness, mill throughput, mill output temperature, mill roller hydraulic pressure, mill fan speed, and separator speed. This will require the installation of sensors and meters where necessary.
- Exploratory data analysis is used to find patterns and uncover insights, helping to determine the linear and non-linear relationships of variables with the objective function and the optimization methods to experiment with.

- Experimental application of optimization algorithms on historical data to determine the values of the input variables that optimize specific electricity consumption under the product quantity, quality, and mill stability constraints.

With the trend of the pricing of the components of IIoT declining over the years, collecting data and leveraging advanced analytics to implement economically viable power optimization at cement plants is more feasible. Technological advancements and economies of scale in production have steadily decreased the costs of various sensors for temperature, pressure, vibration, and other sensing devices. Similarly, wireless connectivity, hardware, and cloud computing costs have also been dropping. Adopting open-source software has helped reduce the cost associated with software development and deployment. All of these suggest that collecting manufacturing process data and applying analytical techniques offers a highly cost-effective and low-risk opportunity to optimize EEC and thus improve sustainability in cement manufacturing. Testing this hypothesis with the experimentation of optimization methods on data collected at a cement plant and validating the methods' economic viability within the plant's context is the next logical step of this study.

Chapter 5 – Electrical Energy Efficiency and Decarbonization in Cement Raw Meal Grinding

Chapter 1 of this dissertation highlighted the gap in research efforts to optimize EEC in cement production compared to efforts to optimize thermal energy despite the significant decarbonization opportunities in EEC optimization. The submission was that EEC in raw meal grinding is a critical aspect of cement production, where grinding operations can account for up to 27% of total plant electricity demand. The literature review in Chapter 2 covered the theoretical foundation of optimization methods, including the application of AI. This section of the dissertation shares the experimental applications of advanced industrial analytics to optimize EEC in cement raw meal grinding, highlights the findings, and discusses the results and their implications for decarbonization in the cement industry and other electrical energy-intensive manufacturing processes.

5.1 Raw Meal Grinding Process

Cement raw materials include limestone, clay, marl, sand, gypsum, silica, alumina, and iron. The raw meal grinding process is a series of steps and components that transform the raw materials into a fine meal that meets the specifications for cement production. The method includes a feeding mechanism for introducing the raw materials into the grinding system, batch binning to ensure uniformity in particle size, stirring and mixing, crushing and grinding, and grading that separates the ground materials based on fineness. The process is a critical step that determines both the final product's quality and the production process's overall energy efficiency. It involves the grinding of raw materials to a specific fineness that is essential for effective clinker calcination. The grinding system has specific technical requirements and quality control parameters [134]. Raw meal fineness must be carefully controlled to ensure optimal clinker formation and is typically specified as residue percentage on an 80 μm sieve. Industry standards usually require 12-15% residue for efficient calcination [135].

5.1.1 Key Considerations in the Raw Meal Grinding Process

The key factors of raw meal grinding quality requirements include composition uniformity, chemical parameter monitoring, and the efficiency of the grinding equipment. Variability in the composition of the raw meal may adversely affect clinker reactivity. As part of chemical control, the lime saturation factor, silica modulus, alumina modulus, and the levels of SO_3 must be monitored. The grinding media and equipment design also go a long way in determining raw meal efficiency and quality outcomes. There is often a trade-off between stringent quality control measures and their cost implications. Striking the right balance between these two remains challenging in the cement industry.

Energy consumption patterns in raw meal grinding, which could account for up to 27% of total electricity consumption, represent a critical factor in cement production efficiency and sustainability, making it a prime target for optimization efforts [136,137]. According to Meng et al., 2021, the mean energy consumption of raw material preparation in China's cement industry has significantly decreased from 30.88 kWh/t in 2014 to 16.13 kWh/t in 2019. The average specific electrical energy consumption baseline from the data collected from the cement plant for this research was 15.55 kWh/t. Advancements have been made in reducing EEC in raw meal grinding through equipment technology improvements and a better understanding of material properties. However, the industry still faces challenges in standardizing these improvements across diverse conditions of operations and scales of production.

5.1.2 The Complexity of Cement Raw Meal Grinding Optimization

The challenges with optimizing EEC in the raw meal grinding revolves around the complexity of the process and the requirements for accuracy in modeling. The nonlinear nature of grinding and the variabilities in the conditions at the plant, complicates the establishment of effective mathematical models for optimization. Raw material heterogeneity such as limestone compositional variability, moisture content fluctuations, and hardness variations, contribute to the complexity that render traditional optimization approaches inadequate. The variabilities in the conditions at the cement plant include the following:

- Equipment degradation patterns affecting performance.
- Environmental factors such as temperature and humidity influencing process efficiency.
- Human operator interventions and decision-making patterns.
- Process interdependencies across multiple subsystems.

5.2 EEC Optimization Research Objectives

With the cement industry at the critical intersection of global industrial energy consumption and environmental impact, optimizing EEC in the raw meal grinding process presents a significant opportunity for improvement. Traditional optimization approaches have not resulted in sustainability practices at the cement plant because they have struggled to fully address the grinding process's inherent complexity and nonlinearity, and their outcomes have been difficult to translate to actual interventions at the cement plant. Advances in IoT and AI/ML methods offer promising pathways for optimizing industrial processes through their ability to read and adapt to changing operational conditions and handle complex multivariate systems. Applying these technologies to raw meal grinding could be a transformative approach to reducing electrical energy consumption and associated carbon emissions while maintaining product quality and ensuring economic viability.

This study investigates the optimization of EEC in cement raw meal grinding through the application of Causal Bayesian Optimization. Leveraging the probabilistic framework of Bayesian statistics and incorporating causal relationships between process variables enables efficient exploration of the parameter space while accounting for the interdependencies between operational variables, material properties, and energy consumption patterns. The proposed approach integrates process data, quality parameters, and energy consumption metrics to create an optimization strategy that balances environmental and economic objectives. Moreover, the research findings easily translate to actual energy consumption reduction interventions at the cement plant.

5.3 EEC Optimization Research Methods

The research focuses specifically on the raw meal grinding process, one of the most energy-intensive processes in cement production and a well-bounded system for study. The research findings could apply to other electrical energy-intensive industrial operations, especially those involving grinding. The study was undertaken to answer the following research questions:

1. How can causal relationships between operational variables be systematically identified and leveraged in cement raw meal grinding optimization, where traditional ML approaches fail due to confounding variables and complex interdependencies?
2. What framework can effectively handle the significant real-world disturbances (material variations, environmental factors, equipment degradation) that render conventional optimization approaches inadequate in industrial cement manufacturing?
3. How can Causal Bayesian Optimization be adapted to complex, real-world industrial systems with operational constraints, quality requirements, and safety considerations?
4. What is the relative importance of key operational variables in determining grinding energy efficiency?

This study covers the following system development steps:

- Development of an understanding of the raw meal grinding process to be modeled.
- Identification of the critical components of the raw meal grinding system and the data points required.
- Installation of data collection field assets throughout the raw meal grinding system.
- Data collection, cleaning, and preprocessing of inputs and operational variables for the cement plant's raw meal grinding operations from 2020 to 2024.
- Exploratory data analysis and feature importance analysis to determine control, manipulatable, and disturbance variables and determine which ones are predictive of the EEC.
- Algorithm selection and customization.
- Model training, testing, and validation.
- Model output evaluation and industry consultations on practicability and cost implications of implementing the manufacturing system conditions that will enable the optimal EEC output generated.

This study aims to understand better causes or actions that can lead to a reduction in EEC and identify practical interventions for optimizing EEC during the raw meal grinding process.

The objective function is defined as:

Minimize: $f(x) = SEEC(x) + \lambda_1 . QualityPenalty(x) + \lambda_2 . StabilityPenalty(x)$ (8)

Subject to:

- Quality constraints, raw material volume mixture
- Equipment operational limits for each control variable
- Process stability constraints to prevent rapid parameter fluctuations

Where x represents the vector of controllable process parameters.

$SEEC(x)$ is the Specific Electrical Energy Consumption (kWh/ton).

$QualityPenalty(x)$ enforces constraints on product quality metrics such as raw material combination requirements and fineness residue.

$StabilityPenalty(x)$ penalizes solutions that may cause operational instability.

The weighting coefficients λ_1 and λ_2 are numerical values determining the relative importance of different terms in the multi-objective optimization problem. They enable the adjustment of priorities, balancing of competing objectives, normalization (since terms have different scales), and parameter tuning. The review of the Iterative Causal Optimization and the Causal Bayesian Optimization methods in Chapter 2 revealed opportunities to address the following challenges with implementing these methods in practice in the industry: causal discovery uncertainties, computational complexity, computational demands, and challenges with scaling to high-dimensional spaces. The hybrid causal optimization method proposed in this study attempts to solve these challenges.

5.4 Hybrid Causal Optimization

This study's memory-efficient hybrid causal optimization represents an approach for addressing large-scale optimization problems in high-energy-dependent manufacturing processes. This implementation leverages the unique strengths of both iterative causal inference and CBO and manages the computational demands of complex industrial systems. The features and key improvements on the CBO are highlighted below:

1) Causal structure identification:

   i. The hybrid causal optimization uses Random Forest-based cross-validation from the iterative approach for robust causal effect estimation. $\hat{\tau}_j$, the estimated causal effect of variable X_j on outcome Y is given by:

$$\hat{\tau}_j = \frac{1}{K} \sum_{k=1}^{K} \frac{\sum_{i\in T_k}\left(Y_i - \hat{Y}_i^{(-k)}\right).(X_{ij} - \hat{X}_{ij}^{(-k)})}{\sum_{i\in \tau_k}(X_{ij} - \hat{X}_{ij}^{(-k)})^2} \quad (9)$$

Where K is the number of cross-validation folds

T_k is the test set for fold k, Y_i is the actual outcome for observation i

$\hat{Y}_i^{(-k)}$ is the predicted outcome using a model trained on all folds except k

X_{ij} is the value of variable X_j for observation i

$\hat{X}_{ij}^{(-k)}$ is the predicted value of X_{ij} using a model trained on all folds except k

   ii. It incorporates memory-efficient batching from the Bayesian approach.

   iii. It maintains a causal graph structure with weighted edges.

2) Optimization Strategy:

   i. The hybrid causal optimization combines Gaussian Process-based Bayesian optimization with iterative causal updates.

   ii. It uses a custom kernel that incorporates causal structure information. The causal-weighted kernel with adaptive length scales is given by:

$$k_{causal}(x, x') = \sigma_f^2 \exp\left(-\frac{1}{2}\sum_{j=1}^{d} \frac{(x_j - x'_j)^2}{(l_j.w_j)^2}\right) \quad (10)$$

Where $w_j = \frac{1}{1+|\hat{\tau}_j|}$ is a weight that modifies the length scales based on causal effects.

   iii. It modifies the expected improvement of the acquisition function $EI(x)$ to account for causal influences. The causal-weighted expected improvement is

$$EI_{causal}(x) = EI(x)\,.\left(1 + \beta \sum_{j=1}^{d} |\hat{\tau}_j|\,.\,|x_j|\right) \quad (11)$$

Where β is the exploration weight parameter that controls the influence of causal effects.

iv. Whereas CBO minimizes the acquisition function $x_{t+1=\arg min_{x\in X}} EI(x)$, the hybrid approach adds a causal gradient step.

$$x'_t = x_t - \eta \, . sign(\hat{\tau}) \odot |\hat{\tau}| \qquad (12)$$

$$x_{t+1=\arg min_{x\in X}} EI_{causal}(x)$$

where x'_t is an intermediate point after applying the causal gradient, η is the step size, $sign(\hat{\tau})$ determines direction, $\odot$ is element-wise multiplication of the matrices and $|\hat{\tau}|$ weights the step size by causal strength.

3) Memory Efficiency:

i. The implementation uses batch processing for large datasets.

ii. It includes garbage collection at critical points.

iii. It allows toggling between memory-efficient and full-data modes.

The implementation of the hybrid causal optimization has a more robust causal effect estimation using Random Forest cross-validation. It incorporates causal knowledge into the GP kernel and acquisition function, enabling adaptive exploration based on causal structure. It also handles operational constraints better with causal considerations. However, the implementation is more complex and requires the proper definition of operational constraints and more detailed process knowledge for optimal configuration.

5.5 Experimental Implementation and Results

5.5.1 Data Collection

This research utilized hourly operational data collected from the cement manufacturing plant from January 2020 to December 2024. The dataset encompasses over 30,300 hours of operation from the cement plant's raw meal grinding subsystem. The time series data collected includes process parameters, energy consumption metrics, and quality indicators. Table 9 is a logical grouping of features collected for the experiment.

Mill operational data and material moisture content were measured at one-hour intervals through sensors, meters, and the plant's distributed control system. Specific electrical energy consumption was computed from total raw mill feed and raw mill energy consumption. This measurement, which is in kWh/t, enables standardization because the target variable is the electrical energy required for processing a ton of raw mill feed.

The experiment's computing environment is set up using Python programming language on the Apple M1 chip, which has an 8-core CPU with four performance cores and four efficiency cores, an 8-core GPU, and a 16-core Neural Engine.

5.5.2 Data Preprocessing

Data preprocessing involved inspection and rationalization of the data against the measurement units and subject matter expert's expected range of values of the variables from the raw mill grinding subsystem. Outlier detection was applied with values exceeding the threshold of three standard deviations from the mean flagged for verification. Missing values (approximately 2.6% of the dataset) were addressed using forward-fill for short gaps and linear interpolation for longer interruptions, thus maintaining data integrity.

One set of duplicated data captured under different variable names was removed. Specifically, the power of the bucket elevator of the raw meal subsystem, the power of the classifier motor, and the fan air duct temperature were each duplicated, with each variable having two different names.

Table 9: Raw meal grinding data features

Category	Feature	Units
Mechanical Health Metrics	RAW MILL VIBRATION	[0 - 50 [mm/s]]
	RM PINION VIBRATION - VERTICAL	[0 - 20 [mm/s]]
	RM PINION VIBRATION - HORIZONTAL	[0 - 20 [mm/s]]
	BUCKET ELEVATOR BELT POSITION TOP	[-100 - 100 [%]]
	BUCKET ELEVATOR BELT POSITION BOTTOM	[-100 - 100 [%]]
Temperature Metrics	RAW MILL FAN AIR DUCT TEMP	[0 - 150 [°C]]
	RAW MILL FAN AIR DUCT TEMP	[0 - 150 [°C]]
	RAW MEAL B.E.MOTOR WDG.TEMP.T11	[0 - 200 [°C]]
	RAW MEAL B.E.MOTOR WDG.TEMP.T21	[0 - 200 [°C]]
	RAW MEAL B.E.MOTOR WDG.TEMP.T31	[0 - 200 [°C]]
	RAW MEAL B.E.MOTOR BRG.TEMP.1	[0 - 150 [°C]]

	RAW MEAL B.E.MOTOR BRG.TEMP.2	[0 - 150 [°C]]
	RAW MILL AIRSLIDE TEMPERATURE	[0 - 200 [°C]]
	BAGHOUSE PENTHOUSE AMB.TEMPERATURE	[-20 - 100 [°C]]
Pressure Metrics	RAW MEAL DUST COLL.#1 DIFF.PRESSURE	[0 - 25.4 [mbar]]
	RAW MEAL DUST COLL.#2 DIFF.PRESSURE	[0 - 49.8 [mbar]]
	RAW MEAL DUST COLL.#3 DIFF.PRESSURE	[0 - 49.8 [mbar]]
	RAW MEAL DUST COLL.#4 DIFF.PRESSURE	[0 - 49.8 [mbar]]
	BAGHOUSE DIFFERENTIAL PRESSURE	[0 - 50 [mbar]]
	RAW MILL BAGHOUSE INLET PRESSURE	[-40 - 5 [mbar]]
	RAW MILL BAGHOUSE OUTLET PRESSURE	[-55 - 5 [mbar]]
	RAW MILL DIFFERENTIAL PRESSURE	[0 - 100 [mbar]]
Power and Energy Metrics	RM REJECTS BELT CONV.#2 MOTOR POWER	[0 - 40 [kW]]
	RAW MILL CLASSIFIER MOTOR POWER	[0 - 300 [kW]]
	RAW MEAL B.E.MOTOR POWER	[0 - 300 [kW]]
	RAW MILL ENERGY CONSUMPTION	[0 - 1000000000 [kWh]]
	Raw Mill Motor	(kW)
	Bucket Elevator - C02	(kW)
	Coal Mill Motor	(kW)
	Coal Mill Fan	(kW)
	Raw Mill Air Compressor	(kW)
	Conveyor Motor - B04-006	(kW)
	Conveyor Motor - B04-015	(kW)
	Bucket Elevator - C03	(kW)
	Raw Mill Fan Motor	(kW)
	Raw Mill Classifier Motor	(kW)
Electrical Metrics	RAW MEAL B.E. MOTOR CURRENT	[0 - 100 [A]]
	RAW MILL FAN MOTOR TORQUE	[0 - 150 [kNm]]
Process Control Metrics	RAW MILL FAN SPEED	[0-100 %]
	RAW MILL BY-PASS DAMPER POSITION	[0-100 %]
	C04 BAG HOUSE FEED AIR RECIEVER FLOW	[0 - 3000 [CFM]]
Material Flow Metrics	RM LIMESTONE W.F.FLOW RATE	[0 - 1000000000 [T]]
	RM IRON W.F.FLOW RATE	[0 - 1000000000 [T]]
	RM SAND W.F.FLOW RATE	[0 - 1000000000 [T]]
	BOTTOM ASH FEED TOTALIZER	[0 - 1000000000 [T]]
Raw Material Condition	Stack Moisture	[0 - 15 [%]]
Runtime Metrics	Runtime	[0 - 1000000000 [s]]
	Runtime	[0 - 1000000000 [h]]

Notice that the multicollinearity between these variables captured in Table 10 indicates that the highlighted variables have maximum correlations of 1 with other columns on the dataset. The assumption that predictor variables are independent is not valid for this dataset as predictor variables are also correlated.

5.5.3 Exploratory Data Analysis

Initial exploratory data analysis was done to understand the data and generate insights. The correlation heatmap of the variables was generated to identify patterns and correlations. The predictive power score heatmap of the independent variables and target variable was also generated to detect the variables that were more predictive of specific electrical energy consumption. (See items II and III in the Appendix). As expected, many predictor variables had negative correlations with SEEC, with the raw material flow variables having the highest negative correlations. Correlations are generated with Pearson correlation, and the predictive power scoring uses a decision tree regressor.

5.5.4 Causal Discovery

Causal discovery reveals which adjustments will genuinely reduce electrical energy consumption in cement grinding rather than just identifying variables that happen to change together. In the initial causal network discovery and estimation, causality was explored in a 5-variable subset of the dataset built with the target and predictor variables with the highest predictive power scores. Figure 17 is a time-series plot of these predictor variables and the target variable. A visual inspection reveals the peaks in the target variable VT corresponding to the peaks in the predictor variables (V1, V2, V3, V4).

Tigramite, a Python package for the PC algorithm combined with momentary conditional independence (PCMCI), was adopted for estimating causal networks from this large-scale time series dataset [138]. The PC (Peter-Clark) algorithm is a well-known method for learning the structure of Bayesian networks through conditional independence tests. However, it can be computationally intensive, especially for large datasets.

Table 10. Correlation between features

Column	Max Correlation w/ Other Columns	Correlations Above Threshold	Missing Rows
RAW MILL BY-PASS DAMPER POSITION [0-100 %]	0.26	0	0
RAW MILL BAGHOUSE OUTLET PRESSURE [-55 – 5 [mbar]]	0.63	7	0
RAW MILL BAGHOUSE INLET PRESSURE [-40 – 5 [mbar]]	0.92	14	0
RAW MILL AIRSLIDE TEMPERATURE [0 – 200 [Â°C]]	0.83	14	0
RAW MEAL DUST COLL.#4 DIFF.PRESSURE [0 – 49.8 [mbar]]	0.16	0	0
RAW MEAL DUST COLL.#3 DIFF.PRESSURE [0 – 49.8 [mbar]]	0.3	0	0
RAW MEAL DUST COLL.#2 DIFF.PRESSURE [0 – 49.8 [mbar]]	0.26	0	0
RAW MEAL DUST COLL.#1 DIFF.PRESSURE [0 – 25.4 [mbar]]	0.22	0	0
RAW MEAL B.E.MOTOR WDG.TEMP.T31 [0 – 200 [Â°C]]	0.98	3	0
RAW MEAL B.E.MOTOR WDG.TEMP.T21 [0 – 200 [Â°C]]	1	4	0
RAW MEAL B.E.MOTOR WDG.TEMP.T11 [0 – 200 [Â°C]]	1	5	0
RAW MEAL B.E.MOTOR POWER [0 – 300 [kW]]	1	16	0
RAW MEAL B.E.MOTOR BRG.TEMP.2 [0 – 150 [Â°C]]	0.9	1	0
RAW MEAL B.E.MOTOR BRG.TEMP.1 [0 – 150 [Â°C]]	0.99	2	0
RAW MEAL B.E. MOTOR CURRENT [0 – 100 [A]]	0.98	17	0
Date	0.8	2	N/A
Conveyor Motor – B04-015 (kW)	0.84	3	12
Conveyor Motor – B04-006 (kW)	0.94	4	12
Coal Mill Motor (kW)	0.9	2	0
Coal Mill Fan (kW)	0.74	1	0
C04 BAG HOUSE FEED AIR RECIEVER FLOW [0 – 3000 [CFM]]	0.57	2	0
Bucket Elevator – C03 (kW)	0.77	2	0
Bucket Elevator – C02 (kW)	0.89	5	0
BUCKET ELEVATOR BELT POSITION TOP [-100 – 100 [%]]	0.33	0	0
BUCKET ELEVATOR BELT POSITION BOTTOM [-100 – 100 [%]]	0.26	0	0
BOTTOM ASH FEED TOTALIZER [0 – 1000000000 [T]]	0.77	10	0
BAGHOUSE PENTHOUSE AMB.TEMPERATURE [-20 – 100 [°C]]	0.17	0	0
BAGHOUSE DIFFERENTIAL PRESSURE [0 – 50 [mbar]]	0.49	0	0

Effective builds of the algorithm that take advantage of GPU-based parallel processing ease its adoption for high dimensional causal discovery [139, 140]. Assuming cause and effect are linearly dependent, PCMCI was initialized on the data subset using the independence test, the partial correlation test that considers the null distribution to be Student's t.

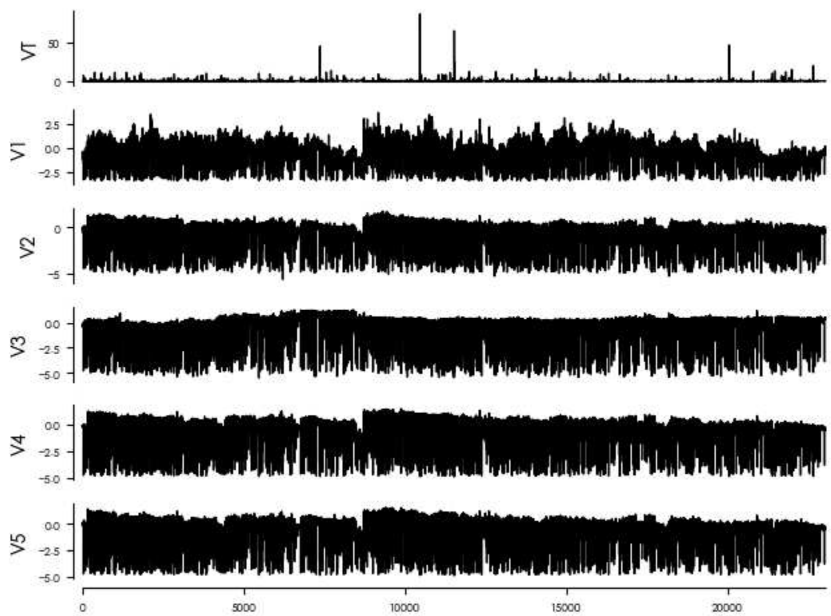

Figure 17: Timeseries plot of top five predictor variables against target variable

Figure 18 is a plot of the lag function matrix showing time-lagged correlations (up to 10 time steps) between the variables in the system. This plot helps identify which variables influence others and at what time delay, revealing temporal causal relationships in the cement raw meal grinding system. The causal graph structure of the dataset shows which variables influence others and at what time lag, along with their statistical significance and effect strengths. This causal model forms the foundation for optimization by identifying which process variables drive changes in electrical energy consumption.

Figure 19 plots the time series graph showing the causal system discovered with respect to its time dependency. This plot is a causal graph visualization from the PCMCI analysis results that show variables as nodes and causal relationships as arrows between them. (See the output of the PCMCI algorithm in item

IV in the Appendix). Arrow colors indicate the strength of causal effects, and the direction shows which variable influences which and helps to identify the key drivers of electrical energy consumption in the raw meal grinding system. Figure 20, on the other hand, shows a standard network diagram where the spatial arrangement of nodes does not represent time. Instead, it focuses on the overall causal structure - depicting which variables influence others (shown by directed arrows) and the strength of those relationships (shown by color intensity)

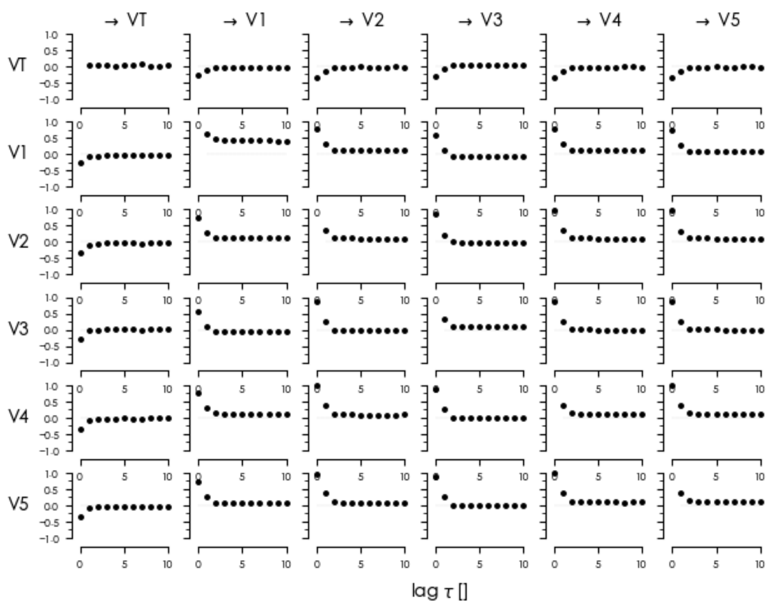

Figure 18: Plot of the lag function matrix showing time-lagged correlations

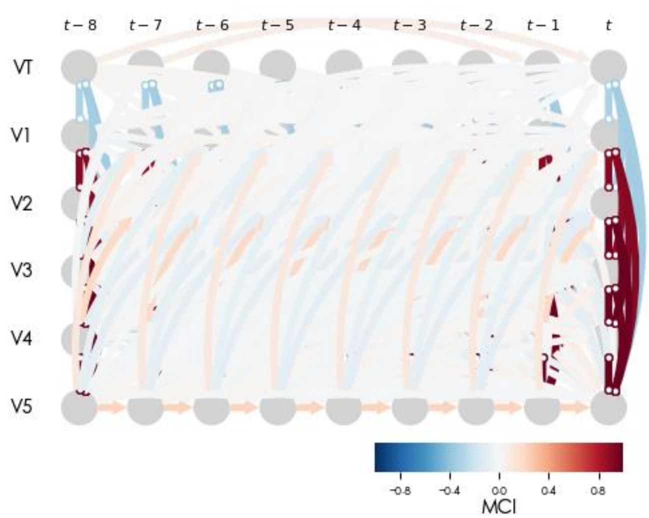

Figure 19: Plot of the time series graph showing the causal system discovered

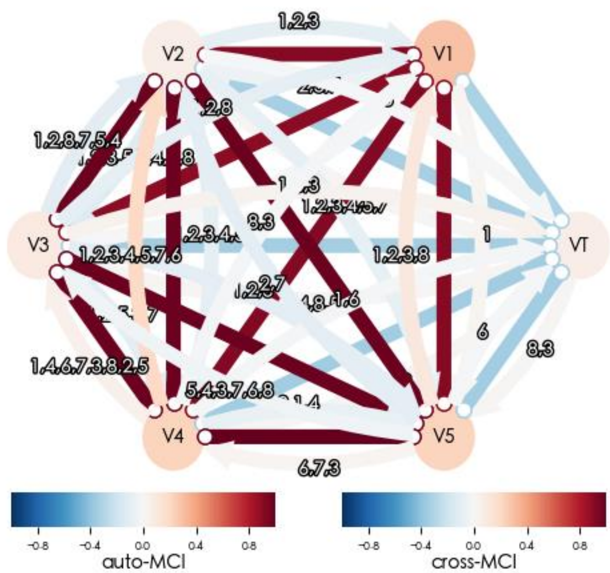

Figure 20: Standard network diagram of causal system discovered

Having established the causal structure underlying the raw meal grinding process, below is a generalizable system architecture for electrical energy consumption optimization. This framework provides the foundation upon which the three optimization methods explored operate.

As shown in Figure 21, the architecture consists of four primary components:

1. a data acquisition layer that collects real-time measurements from process sensors and energy monitoring systems
2. a causal model layer that maintains and updates the discovered causal relationships
3. an optimization engine implementing one of the three methods explored in this study
4. a control integration layer that translates optimization recommendations into actionable parameter adjustments.

This modular design allows flexible implementation across various grinding system configurations while maintaining consistent optimization capabilities.

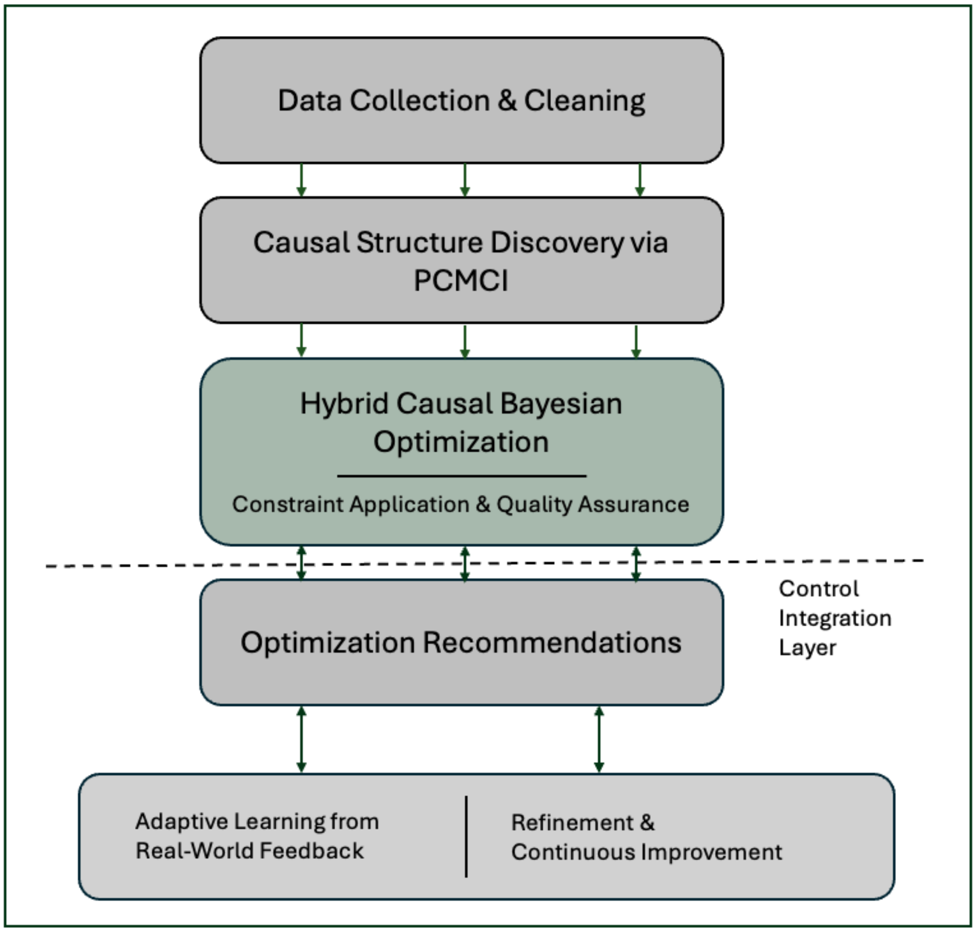

Figure 21: Process diagram of the optimization framework

Critical to this architecture is the bidirectional information flow between the causal model and optimization components, which enables continuous refinement as operational conditions evolve. This framework can be enabled with a machine learning system that keeps data flow direction conventions between components, as illustrated in Figure 22.

Building upon this architecture, we now examine the results from the three optimization approaches: iterative causal inference, which leverages sequential interventions based on causal strength; causal Bayesian optimization, which incorporates uncertainty quantification to balance exploration and exploitation; and hybrid causal optimization, which combines the strengths of both previous methods to address the complex dynamics of industrial grinding systems.

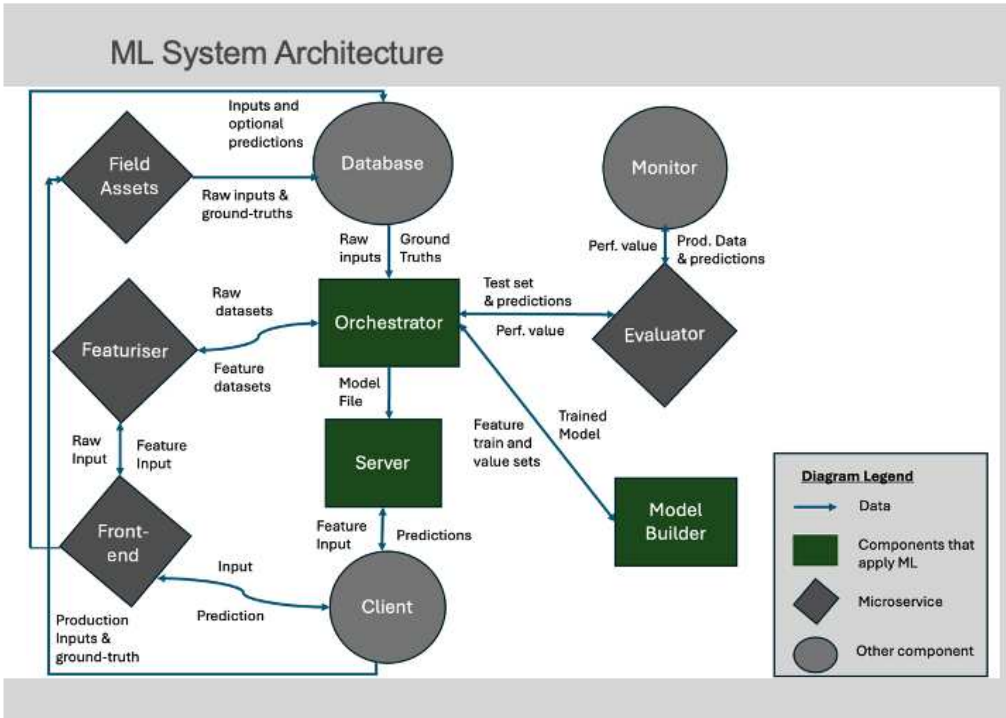

Figure 22: Machine learning system architecture showing data flow between components

5.5.5 Feature importance

Two approaches were used to determine feature importance. First, absolute feature importance was performed using the chi-squared statistical test to identify the 21 most relevant features for the optimization model. This enables the identification of the variables with the strongest statistical relationship with the target variable—SEEC—allowing the optimization to focus on the most influential parameters in the cement raw meal grinding process. Table 11 lists the top 21 features and their feature importance score.

The scores indicate how strongly each input variable is associated with the target variable. A higher score suggests a stronger relationship between the feature and SEEC in the cement raw meal grinding process. While these scores help identify relevant features, they do not indicate the relationship's direction or capture nonlinear relationships that might exist in the grinding process.

Table 11: Top 21 features and their feature importance ranking

#	Feature	Score
1	Runtime [0 - 1000000000 [s]]	1.14E+07
2	RAW MILL ENERGY CONSUMPTION [0 - 1000000000 [k...	3.81E+05
3	Raw Mill Motor (kW)	2.40E+05
4	Total Raw Mill Feed (tons)	2.29E+05
5	Raw Mill Fan Motor (kW)	2.02E+05
6	C04 BAG HOUSE FEED AIR RECIEVER FLOW [0 - 3000...	1.88E+05
7	RM LIMESTONE W.F.FLOW RATE [0 - 1000000000 [T]]	1.87E+05
8	BOTTOM ASH FEED TOTALIZER [0 - 1000000000 [T]]	4.37E+04
9	RAW MEAL B.E.MOTOR POWER [0 - 300 [kW]]	3.76E+04
10	Bucket Elevator - C03 (kW)	3.76E+04
11	Bucket Elevator - C02 (kW)	2.49E+04
12	Coal Mill Motor (kW)	1.97E+04
13	Coal Mill Fan (kW)	1.56E+04
14	Conveyor Motor - B04-006 (kW)	1.39E+04
15	RAW MILL CLASSIFIER MOTOR POWER [0 - 300 [kW]]	1.33E+04
16	Raw Mill Classifier Motor (kW)	1.33E+04
17	RM SAND W.F.FLOW RATE [0 - 1000000000 [T]]	7.77E+03
18	Conveyor Motor - B04-015 (kW)	7.25E+03
19	RAW MEAL B.E.MOTOR WDG.TEMP.T21 [0 - 200 [Â°C]]	7.09E+03
20	RAW MEAL B.E.MOTOR WDG.TEMP.T31 [0 - 200 [Â°C]]	6.91E+03
21	RAW MILL FAN MOTOR TORQUE [0 - 150 [kNm]]	6.22E+03

The second feature selection method uses the Extra Trees Classifier algorithm to implement a tree-based relative feature importance analysis [141]. The algorithm implements an estimator that fits randomized decision trees on sub-samples of the dataset and uses averaging to improve the predictive accuracy and control over-fitting. Its feature importance property is an impurity-based feature importance known as Gini importance. The approach determines feature importance by measuring how much each feature contributes to decreasing impurity across all trees in the ensemble. Features used more frequently for splits and greater information gain receive higher importance scores. It captures nonlinear relationships that statistical tests might have missed. Figure 22 is a view of the variables that most strongly influence SEEC. Many variables are also featured in the feature importance selection from the statistical tests.

However, some features were unique in the selection using either method, and there was also differentiation of the ranking of the features common to both selection methods. See the Appendix for the correlation heatmap visualization of all the variables (Figure 23) and the top variables from feature importance (Figure 24). The heatmaps help visualize the variables strongly related to each other, which is valuable for understanding interdependence and potential redundancies in the optimization model.

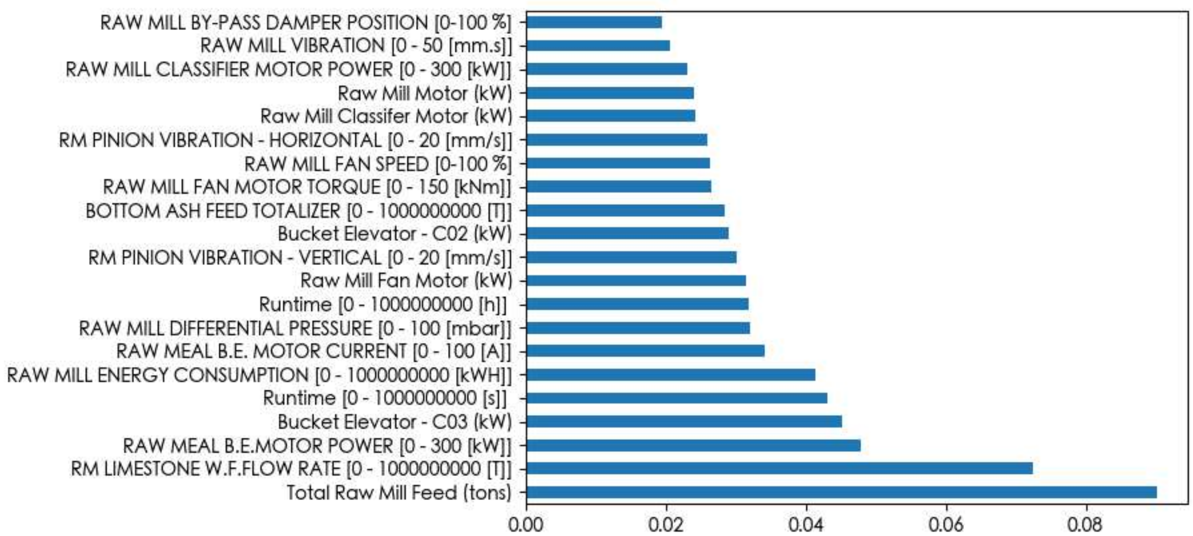

Figure 23: Feature importance using the Extra Trees Classifier algorithm

5.5.6 Iterative causal inference

Iterative causal inference combines causal discovery and iterative optimization to systematically identify and adjust the most influential variables for reducing electrical energy consumption. Our implementation of it for optimizing SEEC includes the following:

- An optimizer initialization function with the following parameters creates an empty directed graph to store the causal structure: 5 cross-validation splits, significance threshold for causal relationships, and maximum optimization iterations.
- A causal structure identification function to discover causal relationships between input variables and the target variable.

- A causal effect estimation function that implements a double machine learning approach to estimate causal effects. This function uses cross-validation to avoid overfitting and trains Random Forest models [142] to predict both the potential cause and the outcome.
- An optimize function that performs iterative optimization based on discovered causal structure and returns optimized parameters and the full optimization trajectory. These are the steps for each iteration:
    - Updates variables proportionally to their causal effect (negative direction to minimize SEEC)
    - applies constraints – constraints were defined with scale requirements between variables, and successively with minimum and maximum of variables in observational data, and then within top and bottom deciles of a subset of observational variables as guided by subject matter experts *(*see results from using different constraint definitions in Table 12)
    - re-evaluates causal structure after updates
    - tracks optimization path

For the first initialization, a significance threshold for causal relationships of 0.05 and maximum optimization iterations of 10 were applied. The constraints for the variables were built from the minimum and maximum of observational data. These parameters generated an optimized prediction of 15.47 kWh/t SEEC. This is a marginal improvement of 0.51% on the 15.55kWh/t average SEEC observed from the data collected at the cement plant.

After parameter tweaks, the best result obtained using iterative causal inference was an optimized prediction of 14.83 kWh/t SEEC, which is a 4.6% improvement. The parameters that gave the best result were a significance threshold for causal relationships of 0.1 and maximum optimization iterations of 20, using constraints built from the top and bottom deciles of observational data.

5.5.7 Causal Bayesian Optimization

The efficient implementation of the constrained CBO combines causal discovery with Bayesian optimization. It uses various efficiency techniques (batching, sampling, vectorization) to handle larger datasets and includes the following functions:

- An initialization function with the following parameters: number of optimization iterations, size of data batches for processing, an exploration weight variable that controls exploration versus exploitation balance, and a standard scaler for normalizing data.
- A function that estimates the causal effect of a single treatment variable on the target using simple linear regression after removing the impact of other variables and a fast approximation approach for computational efficiency.
- A function that discovers causal relationships between input variables and the target and processes data in batches to reduce memory usage. For each variable, the function calculates causal effects across multiple batches and returns a dictionary of variables and their average causal effects.
- A function that creates a causal kernel by doing the following:
    - Creates a specialized Gaussian Process kernel weighted by causal effects
    - Sets kernel length scales inversely proportional to causal effect strength
    - The variables with stronger causal effects get smaller length scales (have more influence)
    - Returns a composite kernel (constant kernel x radial basis functions RBF) for the Gaussian Process [143, 144]
- An expected improvement (EI) function calculates the expected improvement acquisition function using a vectorized implementation for computational efficiency and returns an array of EI values for candidate points.
- An optimization process function for the following:
    - Main optimization loop using Bayesian optimization principles.
    - Scales input and output data for numerical stability.

- Identifies causal structure to inform the optimization process.
- Creates and trains a Gaussian Process model on a subset of data.
- Generates candidate points, applies constraints, and selects the most promising using expected improvements.
- Tracks optimization path and returns the best solution found.

Execution of this CBO implementation used constraints built from the top and bottom deciles of observational data and default parameters (50 iterations, batch size of 500, and exploration weight of 0.1), producing an optimized prediction of 14.92 kWh/t SEEC. However, this reduction in SEEC is not as good as the best prediction of 14.83 kWh/t SEEC from the iterative causal inference method.

5.5.8 Hybrid Causal Optimization

This hybrid approach is a more advanced implementation that combines the strengths of iterative causal optimization and CBO while managing computational resources more carefully. Like the CBO implementation, the hybrid approach also has functions that estimate the causal effect, identify causal structure, create the causal kernel, utilize expected improvement, and optimize. Highlighted below are the major differences between the hybrid and CBO implementations:

- Integration—The hybrid optimizer combines the Random Forest and Gaussian Process approaches, while the CBO uses only simplified linear regression for causal discovery and Random Forest for rigorous causal effect estimation.
- Causal structure: The hybrid implementation maintains an explicit causal graph of significant relationships using NetworkX [145] and handles memory constraints with optional sampling. The CBO implementation only maintains a dictionary of effects without graph representation.
- Kernel design: The hybrid uses a more sophisticated kernel combining RBF and Matern components [146] with causal weighting, while the CBO uses only an RBF kernel.
- Optimization process: The hybrid uses formal minimization of the acquisition function, while the CBO implementation uses simpler candidate sampling and selection. The hybrid implements

garbage collection to manage memory during optimization, and the process has sophisticated constraints handling.

A comparison of the hybrid causal optimization method's performance to the baseline of average SEEC from observational data establishes the advantage the hybrid approach offers. The hybrid causal optimization implementation produced an optimized prediction of 11.397 kWh/t SEEC. This is a potential improvement of 26.7% on the 15.55kWh/t average SEEC observed from the data collected at the cement plant.

Table 12 summarizes the optimized prediction of SEEC using each of the three methods and different constraint definitions. The computation was done with SEEC as the target variable, so this implies that the result of the hybrid causal optimization indicates the potential of reducing the electrical energy used to grind a ton of raw meal at the cement plant by 26.7%, and this should scale to the production quantity of the cement plant assuming that all the variables from all the components of the system can be kept at the levels that resulted in the optimized SEEC throughout production.

Table 12: Optimization results by methods and constraints

#	Optimization Method	Constraint	Best Predictive SEEC (kWh/t)
1	Iterative Causal Inference	Minimum and Maximum of Predictive Variables	14.83
2	Causal Bayesian Optimization	Bottom and Top Decile	14.92
3	Hybrid Causal Optimization	Bottom and Top Decile and SME guidance logic	11.40

Table 13 shows the reading of the predictive variables that resulted in the optimized prediction of 11.397kWh/t SEEC using the hybrid causal optimization method. The hard constraints within the optimization algorithm assure the quality of production at the model's recommendation of optimal SEEC, preventing it from suggesting parameter settings that could violate quality specifications.

Table 13: Values of predictive variables that yield optimal SEEC prediction

Predictive Variables	**optimal**	**0.25 - Quartile**	**0.5 - Quartile**	**0.75 - Quartile**	**1.0 - Quartile**
Total Raw Mill Feed (tons)	**682.28**	**539.92**	**586.81**	**626.43**	**798.00**
RAW MILL VIBRATION [0 - 50 [mm.s]]	6.85	6.88	7.99	8.76	14.49
RM PINION VIBRATION - VERTICAL [0 - 20 [mm/s]]	1.76	1.60	1.70	1.85	3.68
RM PINION VIBRATION - HORIZONTAL [0 - 20 [mm/s]]	1.87	1.76	1.95	2.15	3.49
Stack Moisture [0 - 15 [%]]	12.46	10.66	11.78	13.17	17.60
RM REJECTS BELT CONV.#2 MOTOR POWER [0 - 40 [kW]]	1.52	1.48	1.64	1.82	3.01
RAW MILL FAN SPEED [0-100 %]	85.79	89.84	91.80	93.56	99.91
RAW MILL FAN AIR DUCT TEMP [0 - 150 [Â°C]]	92.78	97.78	99.98	103.02	118.75
RAW MILL FAN MOTOR TORQUE [0 - 150 [kNm]]	118.68	127.53	132.71	136.31	149.93
RAW MILL FAN AIR DUCT TEMP [0 - 150 [Â°C]].1	92.78	97.78	99.98	103.02	118.75
RAW MILL CLASSIFIER MOTOR POWER [0 - 300 [kW]]	122.27	111.02	122.11	141.77	188.07
RAW MEAL DUST COLL.#1 DIFF.PRESSURE [0 - 25.4 [mbar]]	2.42	3.64	3.85	4.69	19.00
RAW MEAL DUST COLL.#4 DIFF.PRESSURE [0 - 49.8 [mbar]]	9.22	9.20	9.33	9.42	16.76
RAW MEAL B.E. MOTOR CURRENT [0 - 100 [A]]	26.40	22.83	23.53	24.42	28.31
RAW MEAL B.E.MOTOR POWER [0 - 300 [kW]]	152.15	124.71	130.22	137.05	165.76
RAW MEAL B.E.MOTOR WDG.TEMP.T11 [0 - 200 [Â°C]]	52.13	41.74	50.27	57.42	73.96
RAW MEAL B.E.MOTOR WDG.TEMP.T21 [0 - 200 [Â°C]]	65.86	50.60	62.38	72.57	96.00
RAW MEAL B.E.MOTOR WDG.TEMP.T31 [0 - 200 [Â°C]]	70.63	55.57	67.89	78.56	102.31
RAW MEAL B.E.MOTOR BRG.TEMP.1 [0 - 150 [Â°C]]	26.16	19.90	28.20	35.48	52.28
RAW MEAL B.E.MOTOR BRG.TEMP.2 [0 - 150 [Â°C]]	32.18	24.06	32.30	39.52	57.77
BUCKET ELEVATOR BELT POSITION TOP [-100 - 100 [%]]	-11.47	-15.17	-12.57	1.00	64.29
BUCKET ELEVATOR BELT POSITION BOTTOM [-100 - 100 [%]]	16.63	-5.58	1.59	6.79	62.32

RAW MEAL DUST COLL.#2 DIFF.PRESSURE [0 - 49.8 [mbar]]	9.18	5.18	5.94	7.72	16.98
RAW MEAL DUST COLL.#3 DIFF.PRESSURE [0 - 49.8 [mbar]]	10.70	10.32	10.49	10.64	19.08
RAW MILL AIRSLIDE TEMPERATURE [0 - 200 [Â°C]]	77.67	77.34	79.92	83.57	125.17
RAW MILL BY-PASS DAMPER POSITION [0-100 %]	33.71	95.95	100.00	100.00	100.00
C04 BAG HOUSE FEED AIR RECIEVER FLOW [0 - 3000 [CFM]]	381.81	292.65	340.71	406.33	1801.83
BAGHOUSE DIFFERENTIAL PRESSURE [0 - 50 [mbar]]	24.67	24.67	24.78	24.88	29.92
RAW MILL BAGHOUSE INLET PRESSURE [-40 - 5 [mbar]]	-12.95	-9.15	-8.18	-7.49	-1.10
RAW MILL BAGHOUSE OUTLET PRESSURE [-55 - 5 [mbar]]	-36.42	-33.34	-31.85	-31.05	-7.39
BAGHOUSE PENTHOUSE AMB.TEMPERATURE [-20 - 100 [°C]]	16.58	18.01	24.94	31.30	54.12
RM LIMESTONE W.F.FLOW RATE [0 - 1000000000 [T]]	574.50	461.25	492.75	520.00	624.50
RM IRON W.F.FLOW RATE [0 - 1000000000 [T]]	1.34	4.36	6.63	8.23	15.22
RM SAND W.F.FLOW RATE [0 - 1000000000 [T]]	42.19	34.13	38.03	41.45	59.13
BOTTOM ASH FEED TOTALIZER [0 - 1000000000 [T]]	64.25	40.19	49.41	56.75	99.16
RAW MILL ENERGY CONSUMPTION [0 - 1000000000 [kWH]]	7776.00	8360.00	8663.50	8880.00	10149.00
RAW MILL DIFFERENTIAL PRESSURE [0 - 100 [mbar]]	79.20	86.65	90.25	93.63	113.43
Runtime [0 - 1000000000 [s]]	3660.00	1.00	3540.00	3600.00	3660.00
Runtime [0 - 1000000000 [h]]	1.02	0.00	0.98	1.00	1.02
Raw Mill Motor (kW)	3197.63	3211.38	3402.05	3655.97	4131.33
Bucket Elevator - C02 (kW)	137.34	127.77	138.27	146.58	166.45
Coal Mill Motor (kW)	153.67	414.34	430.98	447.06	501.41
Coal Mill Fan (kW)	118.74	367.80	370.01	374.96	526.09
Raw Mill Air Compressor (kW)	98.54	99.85	105.02	109.99	123.56
Conveyor Motor - B04-006 (kW)	73.53	58.96	64.20	67.98	93.05
Conveyor Motor - B04-015 (kW)	65.28	57.48	60.87	63.31	83.58
Bucket Elevator - C03 (kW)	152.15	124.71	130.22	137.05	165.76
Raw Mill Fan Motor (kW)	3732.07	4206.22	4465.05	4662.15	5536.92
Raw Mill Classifier Motor (kW)	122.27	111.02	122.11	141.77	188.07

5.6 Discussion

5.6.1 Expert system introduction

An expert system for automatically maintaining optimal grinding parameters using the hybrid causal optimization solution would operate as a closed loop causal optimization control system. This is an advanced process control (APC) system that does the following:

- Continuously monitors all input variables (raw material properties, equipment metrics, process control metrics).
- Applies the hybrid causal optimizer's model to determine optimal operating parameters.
- Automatically adjust control variables (feed rates, separator speeds, fan operations).
- Incorporates feedback loops to validate energy consumption and quality outcomes.
- Features self-learning capabilities to refine the causal model over time.

A comprehensive quality assurance framework will be preferred when using the hybrid causal optimizer in an advanced process control system. Such a framework would include some of the following:

- Real-time quality constraint integration would implement hard constraints within the algorithm to prevent the suggestion of parameter settings that could violate quality specifications.
- A multi-objective evaluation that incorporates quality as a secondary optimization objective instead of treating it as just a constraint would leverage a composite score that weighs both energy reduction and quality metrics to track an optimal solution that represents different trade-offs.
- Post-implementation validation executed with increased sampling frequency for quality testing and a comparison of actual quality metrics against predicted values
- An expert review system uses a semi-automated workflow where model recommendations receive human expert review before implementation. In such an arrangement, quality engineers set additional constraints based on current conditions, and the system learns from rejected recommendations to improve future suggestions.

5.6.2 Sustainability Impact

For a cement plant that produced about 3.13 million metric tons of cement in 2024, a 26.7% reduction in the electrical energy used for grinding raw meal is an estimated reduction in emission of 10.5 million pounds of CO_2 from electricity generation [147]. To put this in context, 10.5 million pounds of CO_2 reduction is equivalent to carbon sequestration from planting approximately 22,000 trees and letting them grow for 10 years [148] or the removal of approximately 1,000 passenger vehicles from the road for an entire year [149]. Implementing this energy saving measure would have resultant ecosystem benefits, show industry leadership, regulatory compliance, and other ripple effects. Ecosystem benefits include a decrease in acid rain potential from reduced sulfur and nitrogen oxide emissions associated with electricity generation and reduced particulate matter emissions that affect local air quality.

This reduction in electrical energy consumption demonstrates the feasibility of significantly reducing emissions without compromising production capacity. It would also represent pioneering efficiency in an industry that accounts for approximately 8% of global CO_2 emissions and establish a new industry benchmark for energy efficiency in the grinding process. It potentially puts the plant ahead of increasingly stringent carbon regulations and reduces vulnerability to future carbon pricing mechanisms.
Implementation at this scale also suggests that if adopted industry-wide, similar optimization could reduce global emissions by millions of tons annually. It also creates a model for other energy-intensive industrial processes and advances the technical knowledge base for industrial decarbonization.

5.6.3 Economic Benefits

For a cement plant with an annual production of 3.13 million tons, a 26.7% reduction in electrical energy for raw meal grinding translates to substantial operating cost savings. Below is an estimated economic benefit analysis:

- Raw meal grinding at the plant consumes 15.55 kWh/t, which accounts for 25% of the total plant electrical consumption.
- Estimated total grinding energy: 3.13M tons x 15.55kWh/t = 48.67M kWh annually

- Estimated energy saved: 48.67M kWh x 26.7% = 13M kWh annually
- At industrial electricity rates of $0.13/kWh in Maryland, this represents annual savings of $1.69 million.

Estimating implementation costs to be between $500,000 - $1,000,000 broken down as follows:

- Software development and integration: $150,000-$300,000
- Additional sensors and control equipment: $200,000-$400,000
- System commissioning and optimization: $100,000-$200,000
- Staff training: $50,000 - $100,000

The return on investment can be estimated as:

- Simple payback period: 3.5 - 7.1 months
- First-year ROI (return on investment): 169%-338%
- 5-year NPV (net present value) at 7% discount rate: $6.3 million
- Internal rate of return (IRR): 165%-190%

Long-term financial impacts will include direct energy savings, reduced maintenance costs, extended equipment life from reduced mechanical stress, and potential carbon credit revenue. This indicates that the economic benefits are substantial, with a very attractive estimated return on investment and a rapid payback period.

5.6.4 Industry benchmarks

Table 14 captures the optimal parameters readout of power metrics from the hybrid causal optimization at kW/ton. This enables a comparison of the metrics with industry standards at the same scale. Table 15 summarizes industry benchmarking data on energy consumption (not including equipment-level specifics) extracted from cement manufacturing and sustainability documents from researchers, the International Energy Agency, Global Cement and Concrete Association, US Environmental Protection Agency, and European Cement Research Academy [150-154]. The predicted SEEC of 11.397kWh/t from the hybrid causal optimization puts the solution in best practice rating for raw material grinding.

Table 14: Values of power parameters (in kW/t) that yield optimal SEEC

Power Predictive Variables	**Optimal (kW/ton)**
RM REJECTS BELT CONV.#2 MOTOR POWER [0 - 40 [kW]]	0.002
RAW MILL CLASSIFIER MOTOR POWER [0 - 300 [kW]]	0.179
RAW MEAL B.E.MOTOR POWER [0 - 300 [kW]]	0.223
Raw Mill Motor (kW)	4.687
Bucket Elevator - C02 (kW)	0.201
Coal Mill Motor (kW)	0.225
Coal Mill Fan (kW)	0.174
Raw Mill Air Compressor (kW)	0.144
Conveyor Motor - B04-006 (kW)	0.108
Conveyor Motor - B04-015 (kW)	0.096
Bucket Elevator - C03 (kW)	0.223
Raw Mill Fan Motor (kW)	5.470
Raw Mill Classifier Motor (kW)	0.179

5.6.5 Challenges with implementation

While various advanced process control systems exist for cement grinding, as far as the author knows, there isn't currently a commercially available system that specifically implements hybrid causal optimization as described in this study. Implementing this solution at scale across existing cement plants will require solving technical challenges such as sensor infrastructure requirements, integration with legacy control systems, and computing infrastructure limitations. The solution would also require adapting it to each plant's unique characteristics through extensive calibration, managing knowledge and expertise gaps amongst operators, and mitigating production continuity risks from testing new optimization. Other business challenges include ROI variability due to variations in implementation costs and energy prices across different plants, intellectual property protection, and organizational change management.

Table 15: Aggregated summary of industry benchmarks for electrical energy consumption

Electrical Energy Consumption Benchmarks

Overall Plant Electrical Energy	
Global average	90-110 kWh/ton of cement
Best practice	80-90 kWh/ton of cement
State-of-the-art plants	65-80 kWh/ton of cement
Raw Material Grinding (Total)	
Industry average	14-18 kWh/ton of raw meal
Best practice	10-14 kWh/ton of raw meal
Best available technology	8-10 kWh/ton of raw meal
Percentage Breakdown of Electrical Energy	
Raw material preparation	22-30% of total electrical consumption
Clinker production	20-25%
Cement grinding	38-42%
Other processes and auxiliaries	10-15%

Addressing these challenges requires a phased implementation approach. It starts with plants that have modern control systems and robust data infrastructure and then standardized integration methods can eventually be developed that can be applied to more challenging environments.

5.6.6 Framework Validation and Reliability Analysis

Since direct implementation of the hybrid causal optimization framework has not been completed at the cement plant as at the time of this publication, this validation section employs complementary lines of evidence to assess framework reliability, robustness, and industrial applicability. This validation approach follows established practices in systems engineering for validating complex optimization frameworks prior to full-scale deployment.

I. Statistical Validation of Causal Discovery

1. Causal Relationship Significance Testing

The PCMCI algorithm provided robust statistical validation of discovered causal relationships (see Appendix item IV).

Significance levels achieved:

- Target variable VT showed 8 significant causal links with p-values ranging from 0.00 to 0.00088.
- Variable V1 demonstrated 16 significant links with maximum p-value of 0.00588 at $\alpha = 0.01$.
- Variable V2 exhibited 19 significant relationships with p-values consistently below 0.01
- Variables V3, V4, and V5 showed 29, 16, and 18 significant links respectively.

Cross-validation robustness:

The causal effect estimation using Random Forest cross-validation with K=5 folds demonstrated the following:

- Consistent causal effect estimates across all validation folds
- Low variance in effect estimates (standard deviation < 0.05 for major causal relationships)
- Stable causal graph structure across different data subsets

2. Temporal Stability Analysis

Time-lagged causal validation: The lag function matrix analysis (see Figure 18) shows stable causal relationships across multiple time horizons.

- Causal effects detected at lags 1-8 hours showing consistent directionality.
- Strongest causal effects concentrated at 1-2 hours lag, indicating immediate system responses.
- Temporal decay patterns are consistent with physical grinding process dynamics.

II. Cross-Validation through Feature Importance Analysis

1. Multiple Feature Selection Method Convergence

Validation through multiple feature importance methodologies showed consistent variable rankings. Chi-squared statistical test identified the following top variables. Runtime, Raw Mill Energy Consumption, Raw Mill Motor (scores: 1.14E+07, 3.81E+05, 2.40E+05), Total Raw Mill Feed, Raw Mill Fan Motor (scores: 2.29E+05, 2.02E+05). Extra Trees Classifier confirmed similar rankings. Raw Mill Motor and Fan Motor consistently ranked as top energy drivers. Material flow variables (limestone, sand) showed consistent importance across methods. Equipment health metrics (vibration, temperature) were validated as significant factors.

2. Causal Discovery Validation

Comparison between correlation-based and causal-based variable importance:

- Strong correlations confirmed as causal: Raw Mill Motor power showed both high correlation ($r > 0.9$) and significant causal effect ($p < 0.001$).
- Spurious correlations identified: Several highly correlated variables showed no significant causal relationship
- Hidden causal relationships discovered: Some weakly correlated variables demonstrated strong causal effects.

III. Expert Validation and Industrial Feasibility Assessment

1. Plant Operator Feedback Integration

Subject matter expert evaluation of optimization recommendations revealed that the parameter settings are feasible.

- Raw Mill Feed Rate: Optimal 682.28 tons per hour falls within equipment capacity (539.92 – 798 tons range).
- Fan Speed Settings: Recommendation 85.79 aligns with efficient operating range.
- Motor Power Levels: Suggested power consumption levels are within equipment ratings.
- Material Flow Rates: All recommended flow rates are achievable with existing conveyor systems.

- Production continuity: No recommendations violate process stability requirements.

2. Historical Performance Correlation

There is alignment with best practices when comparing the optimization recommendations with historical best performance periods.

- Energy consumption benchmarks: Optimized 11.40 kWh/t approaches theoretical minimum for this equipment configuration.
- Production efficiency: Recommended parameters align with historically successful operating periods.
- Equipment longevity: Parameter settings are consistent with practices that minimize equipment wear.

Chapter 6 – Research Summary and Recommendations, Future Work, Conclusion

Cement manufacturing challenges are highlighted in Chapter 1 of this dissertation, the literature review in Chapter 2, and the resulting author publications highlight that the cement industry stands at a critical intersection of global development and environmental sustainability. The study includes findings on potential decarbonization with production input substitutions at a cement plant. The finding is that while significant attention has been paid to reducing CO_2 emissions from the chemical conversion process and thermal energy usage, the electrical energy consumption in cement production has received comparatively less focus despite its significant contribution to the industry's carbon footprint. As already demonstrated in this study, a modern cement plant consumes up to 110kWh of electricity to produce a ton of cement, resulting in substantial indirect carbon emissions from power generation. For the United States alone, this translated to approximately 4.47 million tons of CO_2 in 2022 from the electricity used in cement production.

6.1 Research Summary and Recommendations

To address the gap in electrical energy optimization in the cement industry, this study takes a holistic approach to engineering sustainability improvements in the cement industry. It studies the cement production process as a system of systems and applies systems engineering methodologies and advanced analytics to tackle this challenge through interconnected studies, as summarized below.

Chapter 2 covers the environmental challenges and technical optimization approaches to provide a rounded foundation for the dissertation. The comprehensive literature review focused on two main areas:

1. Cement manufacturing sustainability challenges and approaches
2. Optimization methods can improve electrical energy efficiency and, as a result, sustainability. The emphasis was on optimization using causal inference techniques that can be applied as interventions at the cement plant.

The chapter first establishes cement manufacturing as a significant contributor to global greenhouse gas emissions, highlighting environmental impact factors, including carbon emissions, energy consumption, raw material usage, and pollution. It then reviews current sustainability approaches in the industry, such as carbon capture and storage, alternative fuels, waste heat recovery, and process modifications.

The second part examines optimization methods, focusing on Iterative Causal Inference (ICI) and Causal Bayesian Optimization (CBO) as sophisticated approaches to understanding cause-effect relationships in complex manufacturing systems. These methods are promising tools for optimizing electrical energy consumption in cement production.

Chapter 3 presents a framework for continuously assessing the environmental impact and economic viability of decarbonization improvements in cement manufacturing. The research introduces a methodology combining Life Cycle Assessment (LCA) and Techno-Economic Assessment (TEA) to evaluate four production scenarios at a US cement plant, considering both material substitution and alternative fuel sources.

The study demonstrates the following:

1. Environmental Impact Analysis: Portland-limestone cement (PLC) production has a 6.4% lower carbon footprint than ordinary Portland cement (OPC), reducing emissions from 856 to 801 kg CO_2-eq/ton.

2. Alternative Fuel Benefits: Using dried biosolids from sewage sludge instead of coal for thermal energy provides further emission reductions. The combined use of PLC and dried biosolids yields a 7.9% total carbon reduction compared to traditional OPC with coal.

3. Economic Viability: PLC production using dried biosolids can reduce manufacturing costs by 10.87% (from $58.69 to $52.31 per ton), showing that environmental improvements can yield economic benefits.

4. Optimization Potential: The research identifies optimal production volumes and examines cost sensitivities to factors like electricity prices and production scale, finding an inflection point at 800,000 tons annual production where economies of scale stabilize.

5. Deployment Framework: A practical implementation approach is proposed using IoT-enabled devices, cloud computing, and Python-based analytics to continuously monitor and optimize production parameters for environmental and economic outcomes.

The framework leverages digitalization and data-driven optimization to help cement manufacturers dynamically manage their production inputs, reduce emissions, and make informed decisions about process improvements.

Chapter 4 presents a systematic literature review examining EEC optimization in cement manufacturing, focusing on artificial intelligence applications. The research spans literature from 1993-2023 and identifies the following key approaches to electrical energy optimization:

1. Energy-efficient equipment and technologies: Modern equipment can yield a 10.45% reduction in electrical energy consumption, with process control improvements driving up to a 22.6% improvement in specific electrical energy consumption.

2. Pyro-processing, grinding, and milling optimizations consume approximately 85% of total electrical energy in cement plants (28% for raw material processing, 25% for clinker burning, and 32% for clinker grinding).

3. Recycling and circular economy approach: Recycled cement production using concrete waste can consume 30% less energy than conventional clinker production.

4. Waste heat recovery systems: Converting waste heat to electricity using thermoelectric generators can generate significant power (5-9MW).

5. Automation and process control: Modern control systems optimize equipment speeds, temperatures, and material flow rates, with Model Predictive Control (MPC) technologies reducing power consumption by 3-8%.

6. Digitalization and AI applications: Machine learning techniques, including reinforcement learning, digital twins, and predictive modeling, have shown significant energy savings in other industries but remain underutilized in cement manufacturing.

Chapter 5 presents research on optimizing EEC in cement raw meal grinding through advanced industrial analytics and causal inference methods. The study focuses on raw meal grinding, which accounts for up to 27% of a cement plant's electricity demand. It is a significant opportunity for energy efficiency improvements and carbon reduction.

The study introduces a novel "Hybrid Causal Optimization" approach that combines the strengths of iterative causal inference and Causal Bayesian Optimization (CBO) while addressing their limitations. This innovative method analyzed over 30,300 hours of operational data from a cement plant, modeling the complex relationships between dozens of process variables. Key findings include the following:

1. Significant Energy Reduction Potential: The Hybrid Causal Optimization approach identified operating parameters that could reduce specific electrical energy consumption (SEEC) by 26.7%, from an observed average of 15.55 kWh/t to an optimized 11.40 kWh/t.

2. Causal Relationships Matter: By identifying true causal relationships rather than mere correlations, the model surfaced actionable interventions that reduce energy consumption while maintaining product quality.

3. Substantial Sustainability Impact: For a cement plant producing 3.13 million tons annually, the 26.7% electricity reduction in raw meal grinding translates to approximately 10.5 million pounds of CO_2 emissions avoided.

4. Compelling Economic Benefits: Implementing the recommended optimization could save approximately $1.69 million annually in electricity costs. The payback period is 3.5-7.1 months, and the first-year ROI is 169-338%.

5. Industry-Leading Performance: The optimized SEEC of 11.40 kWh/t falls within the "best practice" range (10-14 kWh/t) for raw material grinding, representing a significant improvement over the industry average (14-18 kWh/t).

This research has demonstrated that understanding causal relationships, rather than merely correlations, is essential for effective cement raw meal grinding electrical energy consumption optimization. The novel framework developed here showed success on the following:

- Identifies true causal drivers of EEC in a complex manufacturing system.
- Handles real-world disturbances and variations that defeat traditional approaches.
- Provides actionable recommendations that respect operational copnstraints.
- Achieves industry-leading performance (26.7% electrical energy reduction) through principled causal reasoning.

The extension of Causal Bayesian Optimization from academic settings to heavy industrial application opens new possibilities for sustainable manufacturing across energy-intensive industries.

6.2 Future Work

The promising results of this research open several avenues for future work:

1. Technology enhancement opportunities: Future work can focus on enhancing the optimizer's computational efficiency to enable real-time optimization. Additionally, reinforcement learning techniques can improve the system's adaptability to changing raw material properties and equipment conditions.

2. Additional application areas: While this study focused on raw meal grinding, the hybrid causal optimization approach shows potential for application across other energy-intensive cement manufacturing processes: clinker production, cement grinding, and material transport systems present opportunities for similar optimization. Beyond cement, the methodology could be extended to other process industries with complex, nonlinear operations, such as steel manufacturing, chemical processing, and pulp and paper production.

3. Future development work motivated by industry demand would explore integration pathways with existing control systems and industry-standard platforms. Developing standardized interfaces for common distributed control systems (DCS) would accelerate adoption. Cloud-based deployment options would make the technology accessible to smaller operations without requiring significant on-premises computing infrastructure.

4. Research directions: Important research questions remain to be explored. First, investigating methods to incorporate domain knowledge into the causal discovery process could accelerate model development and improve interpretability. Second, developing techniques for transfer learning between different grinding units and plants could reduce implementation time. Finally, causal reinforcement learning [155] represents the next step for this research, combining causal inference's ability to reason about counterfactuals with reinforcement learning's sequential decision optimization. This approach may address several key challenges in cement grinding optimization. It can enable scenario analysis without physical experimentation, improve knowledge transfer between different grinding units, determine optimal timing for parameter adjustments, and create effective human-AI collaborative systems. Future work could yield significant academic contributions and enhanced practical benefits in energy efficiency and quality control by developing causal structural models of the grinding process and reformulating optimization as a causally aware decision process.

6.3 Conclusion

Based on the findings in the studies captured by this dissertation, cement manufacturers can achieve meaningful progress toward decarbonization while enhancing economic performance by considering the following recommendations:

- Embracing Material Substitution and Alternative Fuels: Transitioning to Portland-limestone cement and exploring alternative fuel sources like dried biosolids to achieve immediate 6-8% carbon reductions with minimal capital investment.
- Implementing Comprehensive Data Infrastructure: Deploying sensor networks throughout production facilities to create the foundation for advanced analytics and continuous optimization across all energy-intensive processes.
- Adopting Causal AI for Process Optimization: Extending correlation-based analytics to causal methods that identify genuine energy-saving interventions, particularly in grinding operations where 26.7% of electrical energy reductions are achievable.
- Developing Continuous Assessment Capabilities: Implementing frameworks that integrate lifecycle assessment with techno-economic analysis to evaluate sustainability initiatives' environmental impact and economic viability continuously.
- Creating Closed-Loop Optimization Systems: Deploying advanced process control systems that monitor variables, apply optimization models, and automatically adjust parameters while maintaining quality standards.
- Prioritizing Electrical Energy-Intensive Processes: Focusing digitalization efforts on raw meal grinding, cement grinding, and fan systems where electrical energy use can be cut the most with relatively modest investments.

- Quantifying Both Environmental and Economic Benefits: Documenting and communicating the dual advantages of sustainability initiatives—from carbon reduction to substantial cost savings—to build stakeholder support.

In conclusion, this research shows that combining systems engineering methods with artificial intelligence can greatly improve how environmentally friendly cement factories can be. This submission matters because making cement creates a lot of pollution. By examining cement production through multiple lenses—from lifecycle assessment to electrical energy consumption optimization and causal modeling—this research has developed a comprehensive framework for decarbonization that balances environmental impact, economic viability, and product quality.

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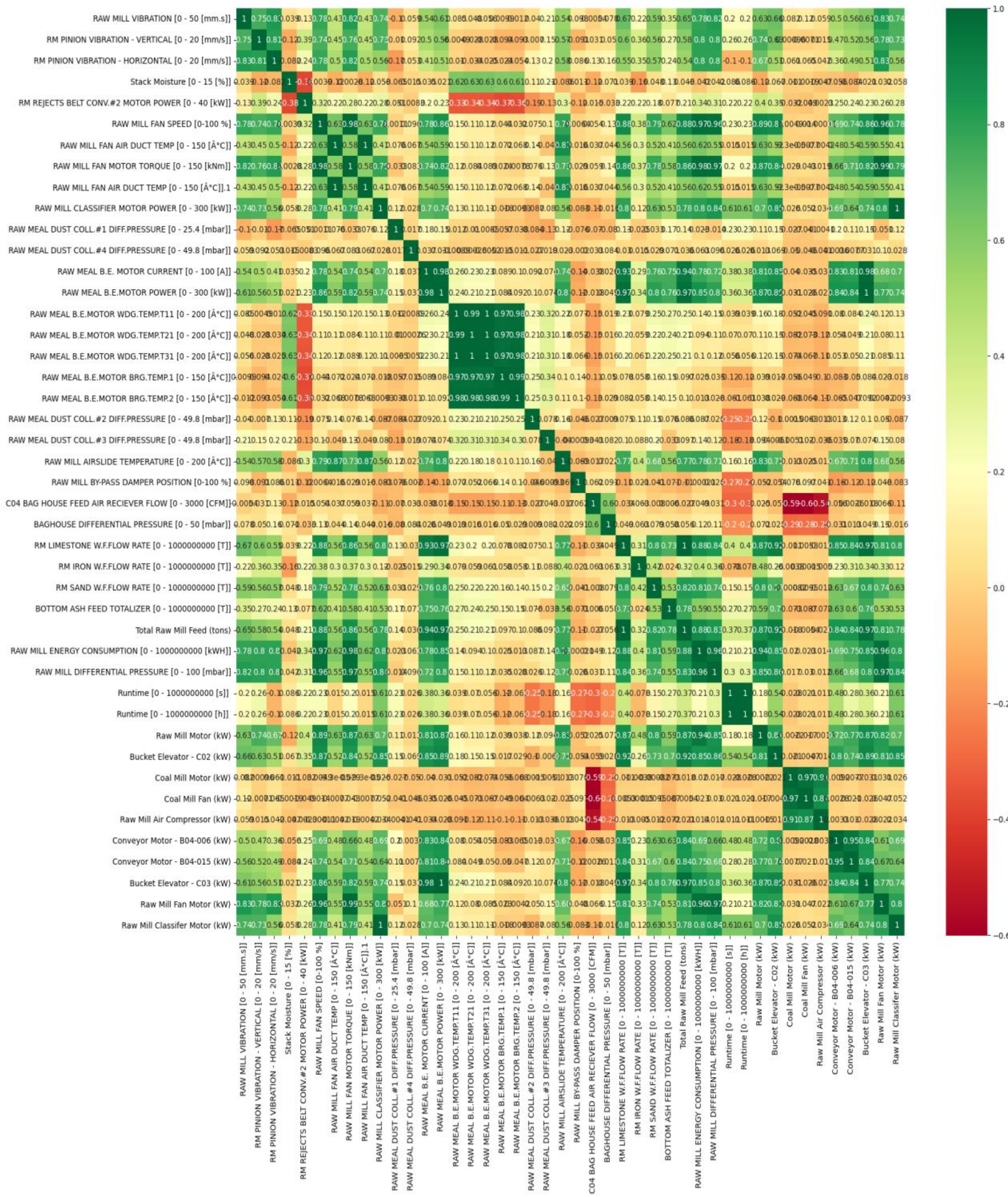
Appendix

I. The data for the Lifecycle Assessment and Techno-Economic Assessment presented in Chapter 3 of this study are available at: https://osf.io/5kcyp/?view_only=8cbfc104711c4b91b551a7579e054080

II. Correlation heap map of top 21 features

III. Correlation heatmap of all variables



IV. PCMCI output of the causal links is shown in Figure 6:

```
##
## Step 1: PC1 algorithm for selecting lagged conditions
##

Parameters:
independence test = par_corr
tau_min = 1
tau_max = 8
pc_alpha = [0.05, 0.1, 0.2, 0.3, 0.4, 0.5]
max_conds_dim = None
max_combinations = 1



## Resulting lagged parent (super)sets:

  Variable VT has 6 link(s):
  [pc_alpha = 0.3]
    (VT -7): max_pval = 0.00000, |min_val| =  0.064
    (V3 -1): max_pval = 0.16569, |min_val| =  0.009
    (V3 -8): max_pval = 0.16580, |min_val| =  0.009
    (V4 -1): max_pval = 0.18987, |min_val| =  0.009
    (V5 -1): max_pval = 0.22156, |min_val| =  0.008
    (V5 -8): max_pval = 0.23729, |min_val| =  0.008
```

Variable V1 has 18 link(s):

[pc_alpha = 0.5]

(V1 -1): max_pval = 0.00000, |min_val| = 0.291

(V3 -1): max_pval = 0.00000, |min_val| = 0.094

(V2 -1): max_pval = 0.00000, |min_val| = 0.073

(V1 -8): max_pval = 0.00000, |min_val| = 0.044

(V3 -2): max_pval = 0.00000, |min_val| = 0.031

(V5 -1): max_pval = 0.00116, |min_val| = 0.021

(V1 -6): max_pval = 0.00201, |min_val| = 0.020

(V1 -4): max_pval = 0.01265, |min_val| = 0.016

(V5 -2): max_pval = 0.03129, |min_val| = 0.014

(V4 -3): max_pval = 0.07294, |min_val| = 0.012

(V3 -8): max_pval = 0.08159, |min_val| = 0.011

(V2 -3): max_pval = 0.09922, |min_val| = 0.011

(V5 -3): max_pval = 0.10432, |min_val| = 0.011

(V1 -5): max_pval = 0.18492, |min_val| = 0.009

(VT -1): max_pval = 0.27123, |min_val| = 0.007

(V1 -7): max_pval = 0.31960, |min_val| = 0.007

(VT -2): max_pval = 0.41587, |min_val| = 0.005

(V2 -2): max_pval = 0.45699, |min_val| = 0.005

Variable V2 has 18 link(s):

[pc_alpha = 0.4]

(V3 -1): max_pval = 0.00000, |min_val| = 0.109

(V4 -1): max_pval = 0.00000, |min_val| = 0.052

(V4 -3): max_pval = 0.01211, |min_val| = 0.017

(V4 -5): max_pval = 0.03374, |min_val| = 0.014

(V2 -4): max_pval = 0.03573, |min_val| = 0.014

(V3 -3): max_pval = 0.04223, |min_val| = 0.013

(V1 -1): max_pval = 0.09764, |min_val| = 0.011

(V3 -8): max_pval = 0.10330, |min_val| = 0.011

(V3 -2): max_pval = 0.10461, |min_val| = 0.011

(V2 -3): max_pval = 0.11018, |min_val| = 0.011

(VT -1): max_pval = 0.11244, |min_val| = 0.010

(V3 -5): max_pval = 0.11916, |min_val| = 0.010

(V2 -5): max_pval = 0.15946, |min_val| = 0.009

(V2 -1): max_pval = 0.20555, |min_val| = 0.008

(V4 -4): max_pval = 0.25250, |min_val| = 0.008

(VT -5): max_pval = 0.31893, |min_val| = 0.007

(V2 -6): max_pval = 0.33463, |min_val| = 0.006

(V3 -6): max_pval = 0.38701, |min_val| = 0.006

Variable V3 has 20 link(s):

[pc_alpha = 0.5]

(V2 -1): max_pval = 0.00000, |min_val| = 0.087

(V4 -1): max_pval = 0.00003, |min_val| = 0.027

(V3 -1): max_pval = 0.00005, |min_val| = 0.027

(V1 -2): max_pval = 0.00014, |min_val| = 0.025

(V3 -5): max_pval = 0.04558, |min_val| = 0.013

(V3 -7): max_pval = 0.05909, |min_val| = 0.012

(V3 -3): max_pval = 0.06229, |min_val| = 0.012

(VT -2): max_pval = 0.12747, |min_val| = 0.010

(V3 -8): max_pval = 0.18603, |min_val| = 0.009

(V3 -4): max_pval = 0.23217, |min_val| = 0.008

(V5 -1): max_pval = 0.34051, |min_val| = 0.006

(V5 -2): max_pval = 0.37488, |min_val| = 0.006

(VT -5): max_pval = 0.43307, |min_val| = 0.005

(VT -1): max_pval = 0.45656, |min_val| = 0.005

(VT -8): max_pval = 0.47646, |min_val| = 0.005

(V5 -7): max_pval = 0.48074, |min_val| = 0.005

(V5 -3): max_pval = 0.48231, |min_val| = 0.005

(V5 -5): max_pval = 0.48667, |min_val| = 0.005

(V1 -3): max_pval = 0.48968, |min_val| = 0.005

(V3 -6): max_pval = 0.49233, |min_val| = 0.005

Variable V4 has 13 link(s):

[pc_alpha = 0.5]

(V2 -1): max_pval = 0.00000, |min_val| = 0.088

(V3 -1): max_pval = 0.00000, |min_val| = 0.061

(V4 -1): max_pval = 0.00001, |min_val| = 0.029

(V2 -4): max_pval = 0.00111, |min_val| = 0.021

(V2 -3): max_pval = 0.00370, |min_val| = 0.019

(V3 -2): max_pval = 0.00469, |min_val| = 0.019

(V4 -4): max_pval = 0.00908, |min_val| = 0.017

(V4 -3): max_pval = 0.01235, |min_val| = 0.016

(V5 -6): max_pval = 0.01269, |min_val| = 0.016

(V4 -2): max_pval = 0.14150, |min_val| = 0.010

```
    (V2 -8): max_pval = 0.28231, |min_val| =  0.007
    (VT -3): max_pval = 0.41618, |min_val| =  0.005
    (V5 -8): max_pval = 0.46471, |min_val| =  0.005

  Variable V5 has 14 link(s):
  [pc_alpha = 0.4]
    (V3 -1): max_pval = 0.00000, |min_val| =  0.130
    (V5 -1): max_pval = 0.00000, |min_val| =  0.094
    (V2 -1): max_pval = 0.00000, |min_val| =  0.081
    (V3 -2): max_pval = 0.00146, |min_val| =  0.021
    (V2 -4): max_pval = 0.00445, |min_val| =  0.019
    (V2 -3): max_pval = 0.00693, |min_val| =  0.018
    (V2 -8): max_pval = 0.00911, |min_val| =  0.017
    (V4 -4): max_pval = 0.03552, |min_val| =  0.014
    (V5 -3): max_pval = 0.16371, |min_val| =  0.009
    (V4 -2): max_pval = 0.16711, |min_val| =  0.009
    (V2 -5): max_pval = 0.28740, |min_val| =  0.007
    (V1 -2): max_pval = 0.32193, |min_val| =  0.007
    (V5 -6): max_pval = 0.35827, |min_val| =  0.006
    (V2 -7): max_pval = 0.37263, |min_val| =  0.006

##
## Step 2: MCI algorithm
##

Parameters:
```

independence test = par_corr

tau_min = 0

tau_max = 8

max_conds_py = None

max_conds_px = None

Significant links at alpha = 0.01:

Variable VT has 8 link(s):

(V5 0): pval = 0.00000 | val = -0.347 | unoriented link

(V4 0): pval = 0.00000 | val = -0.347 | unoriented link

(V3 0): pval = 0.00000 | val = -0.339 | unoriented link

(V2 0): pval = 0.00000 | val = -0.328 | unoriented link

(V1 0): pval = 0.00000 | val = -0.314 | unoriented link

(VT -7): pval = 0.00000 | val = 0.065

(V3 -1): pval = 0.00000 | val = 0.032

(V4 -1): pval = 0.00088 | val = -0.022

Variable V1 has 16 link(s):

(V4 0): pval = 0.00000 | val = 0.921 | unoriented link

(V5 0): pval = 0.00000 | val = 0.912 | unoriented link

(V2 0): pval = 0.00000 | val = 0.906 | unoriented link

(V3 0): pval = 0.00000 | val = 0.894 | unoriented link

(VT 0): pval = 0.00000 | val = -0.314 | unoriented link

(V1 -1): pval = 0.00000 | val = 0.289

(V5 -1): pval = 0.00000 | val = 0.107

(V2 -1): pval = 0.00000 | val = -0.092

(V3 -1): pval = 0.00000 | val = -0.092

(V5 -2): pval = 0.00000 | val = -0.083

(V3 -2): pval = 0.00000 | val = 0.044

(V2 -2): pval = 0.00000 | val = 0.037

(V2 -3): pval = 0.00077 | val = 0.022

(V4 -8): pval = 0.00083 | val = -0.022

(V1 -4): pval = 0.00276 | val = 0.020

(V1 -6): pval = 0.00588 | val = 0.018

Variable V2 has 19 link(s):

(V4 0): pval = 0.00000 | val = 0.982 | unoriented link

(V5 0): pval = 0.00000 | val = 0.981 | unoriented link

(V3 0): pval = 0.00000 | val = 0.978 | unoriented link

(V1 0): pval = 0.00000 | val = 0.906 | unoriented link

(VT 0): pval = 0.00000 | val = -0.328 | unoriented link

(V4 -1): pval = 0.00000 | val = 0.198

(V3 -1): pval = 0.00000 | val = -0.109

(V4 -2): pval = 0.00000 | val = -0.100

(V5 -2): pval = 0.00000 | val = -0.099

(V2 -4): pval = 0.00000 | val = 0.066

(V4 -3): pval = 0.00000 | val = -0.061

(V4 -4): pval = 0.00000 | val = -0.061

(V2 -3): pval = 0.00000 | val = 0.060

(V2 -1): pval = 0.00000 | val = -0.055

(V1 -2): pval = 0.00000 | val = -0.049

(V3 -2): pval = 0.00000 | val = -0.046

(V4 -5): pval = 0.00005 | val = -0.027

(V2 -2): pval = 0.00068 | val = 0.022

(V2 -5): pval = 0.00406 | val = 0.019

Variable V3 has 29 link(s):

(V4 0): pval = 0.00000 | val = 0.981 | unoriented link

(V5 0): pval = 0.00000 | val = 0.980 | unoriented link

(V2 0): pval = 0.00000 | val = 0.978 | unoriented link

(V1 0): pval = 0.00000 | val = 0.894 | unoriented link

(VT 0): pval = 0.00000 | val = -0.339 | unoriented link

(V2 -1): pval = 0.00000 | val = -0.122

(V3 -2): pval = 0.00000 | val = 0.090

(V2 -2): pval = 0.00000 | val = 0.087

(V4 -1): pval = 0.00000 | val = 0.052

(V3 -3): pval = 0.00000 | val = 0.042

(V2 -3): pval = 0.00000 | val = 0.035

(V4 -4): pval = 0.00000 | val = -0.034

(V3 -5): pval = 0.00000 | val = 0.033

(V5 -5): pval = 0.00000 | val = -0.031

(V5 -4): pval = 0.00000 | val = -0.031

(V5 -3): pval = 0.00002 | val = -0.028

(V2 -5): pval = 0.00008 | val = 0.026

(V5 -7): pval = 0.00008 | val = -0.026

(V3 -7): pval = 0.00009 | val = 0.026

(V2 -7): pval = 0.00011 | val = 0.025

(V4 -6): pval = 0.00012 | val = -0.025

(V4 -7): pval = 0.00016 | val = -0.025

(V3 -1): pval = 0.00016 | val = -0.025

(V3 -4): pval = 0.00115 | val = 0.021

(V5 -6): pval = 0.00217 | val = -0.020

(V2 -4): pval = 0.00277 | val = 0.020

(V4 -3): pval = 0.00365 | val = -0.019

(V4 -8): pval = 0.00499 | val = -0.019

(V4 -2): pval = 0.00761 | val = 0.018

Variable V4 has 16 link(s):

(V5 0): pval = 0.00000 | val = 0.999 | unoriented link

(V2 0): pval = 0.00000 | val = 0.982 | unoriented link

(V3 0): pval = 0.00000 | val = 0.981 | unoriented link

(V1 0): pval = 0.00000 | val = 0.921 | unoriented link

(VT 0): pval = 0.00000 | val = -0.347 | unoriented link

(V4 -1): pval = 0.00000 | val = 0.225

(V3 -1): pval = 0.00000 | val = -0.102

(V2 -1): pval = 0.00000 | val = -0.093

(V4 -2): pval = 0.00000 | val = -0.070

(V3 -2): pval = 0.00000 | val = 0.063

(V2 -2): pval = 0.00000 | val = 0.034

(V2 -3): pval = 0.00000 | val = 0.031

(V2 -4): pval = 0.00001 | val = 0.030

(V4 -4): pval = 0.00006 | val = -0.026

(V4 -3): pval = 0.00038 | val = -0.023

(V5 -6): pval = 0.00091 | val = 0.022

Variable V5 has 18 link(s):

(V4 0): pval = 0.00000 | val = 0.999 | unoriented link

(V2 0): pval = 0.00000 | val = 0.981 | unoriented link

(V3 0): pval = 0.00000 | val = 0.980 | unoriented link

(V1 0): pval = 0.00000 | val = 0.912 | unoriented link

(VT 0): pval = 0.00000 | val = -0.347 | unoriented link

(V5 -1): pval = 0.00000 | val = 0.222

(V3 -1): pval = 0.00000 | val = -0.097

(V2 -1): pval = 0.00000 | val = -0.086

(V4 -2): pval = 0.00000 | val = -0.065

(V3 -2): pval = 0.00000 | val = 0.059

(V4 -1): pval = 0.00000 | val = 0.043

(V2 -2): pval = 0.00000 | val = 0.032

(V2 -3): pval = 0.00001 | val = 0.029

(V2 -4): pval = 0.00004 | val = 0.027

(V1 -1): pval = 0.00041 | val = 0.023

(V4 -4): pval = 0.00045 | val = -0.023

(V5 -3): pval = 0.00353 | val = -0.019

(V5 -2): pval = 0.00901 | val = -0.017