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Similarity Assessment of Manufacturing Processes Within and  
Across Sectors

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Associate Supervisor: Mark Jolly

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## **Academic integrity declaration**

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## **Abstract**

The Foundation Industries, namely cement, metals, glass, ceramics, paper, and chemicals, are vital to industrial economies but are also highly resource- and emissions-intensive. Existing sustainability benchmarking approaches often focus on the facility or sector level, which limits their granularity and flexibility needed for targeted, cross-sectoral improvement. This thesis addresses these gaps by developing tools and methods for process-level sustainability benchmarking, enabling transferable and data-driven decision-making.

The research is structured around five objectives, beginning with a systematic review that highlights fragmentation in existing decision-support methods and their limited applicability to sectoral comparisons at the process level. A framework for selecting environmental Key Performance Indicators (KPIs) is then developed and applied to industrial data, which assists in consistent benchmarking of environmental performance. Additionally, shared process examination using an adapted Dependency Structure Matrix (DSM) identified common operations across sectors, revealing opportunities for coordinated interventions. These insights led to the development of Similarity-based Sustainability Assessment (SIMSA), a novel framework that integrates ratio-based normalisation, Monte Carlo-based Multi-Criteria Decision Analysis (MCDA) weighting, and similarity analysis for benchmarking processes both within and across sectors.

The thesis contributes novel methodologies and practical tools, encouraging a shift toward process-centric, cross-sectoral benchmarking. This offers valuable insights for industry and researchers seeking to accelerate sustainable transitions in process manufacturing.

**Keywords:**

Sustainability, benchmarking, foundation industries, process industries, process-level assessment, decision-support tools and similarity assessment.

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# List of Publications

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## Non-Refereed Journal Articles and Conference Publications

- Alfarsi, Z. Sherif, S. Jagtap, and K. Salonitis, “Driving sustainability: Assessing KPI effectiveness in the Saudi chemical industry”, *Discover Sustainability*, 2024.
- S. Sarfraz, Z. Sherif, and K. Salonitis, “Navigating circular economy and digitalisation: A comparative study of manufacturing strategies in the UK and Saudi Arabia”, *Procedia CIRP*, 2024.
- Z. Sherif, J. Patsavellas, and K. Salonitis, “Feasibility of graphene-enhanced strength in sanitary ceramics”, *TMS 2025*, pp. 65–75.
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- S. Sarfraz, Z. Sherif, M. Jolly, and K. Salonitis, “Towards framework development for benchmarking energy efficiency in foundation industries: A case study of granulation process”, *TMS 2023*, pp. 221–233.

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## List of Abbreviations

|                 |                                                                         |
|-----------------|-------------------------------------------------------------------------|
| AHP             | Analytic Hierarchy Process                                              |
| AI              | Artificial Intelligence                                                 |
| AM              | Additive Manufacturing                                                  |
| BAT             | Best Available Technology                                               |
| BF              | Blast Furnace                                                           |
| BREFs           | BAT reference documents                                                 |
| BOF             | Basic Oxygen Furnace                                                    |
| CBAM            | Carbon Border Adjustment Mechanism                                      |
| CCS             | Carbon Capture and Storage                                              |
| CO <sub>2</sub> | Carbon Dioxide                                                          |
| DSM             | Dependency Structure Matrix                                             |
| EAF             | Electric Arc Furnace                                                    |
| ERP             | Enterprise Resource Planning                                            |
| EU              | European Union                                                          |
| EU-BRITE        | European Bureau for Research on Industrial Transformation and Emissions |
| EU ETS          | European Union Emissions Trading System                                 |
| FIs             | Foundation Industries                                                   |
| GDP             | Gross Domestic Product                                                  |
| GHG             | Greenhouse Gas                                                          |
| GJ              | Gigajoule                                                               |
| GRI             | Global Reporting Initiative                                             |
| IEMA            | Institute of Environmental Management and Assessment                    |
| ISO             | International Organization for Standardization                          |
| KPI             | Key Performance Indicator                                               |
| LCA             | Life Cycle Assessment                                                   |
| LCC             | Life Cycle Coasting                                                     |
| LCEA            | Life Cycle Energy Assessment                                            |
| MCDA            | Multi-Criteria Decision Analysis                                        |
| ML              | Machine Learning                                                        |
| OECD            | Organisation for Economic Co-operation and Development                  |
| ORC             | Organic Rankine Cycle                                                   |
| OSW             | Objective Simulation-Based Weighting                                    |
| PRISMA          | Preferred Reporting Items for Systematic Reviews and Meta-Analyses      |
| RPD             | Relative Percent Difference                                             |
| R&D             | Research and Development                                                |
| SDG             | Sustainable Development Goals                                           |

|        |                                                                   |
|--------|-------------------------------------------------------------------|
| SLR    | Systematic Literature Review                                      |
| SIMSA  | Similarity-based Sustainability Assessment                        |
| TBL    | Trible Bottom Line                                                |
| TOPSIS | Technique for Order of Preference by Similarity to Ideal Solution |
| UK     | United Kingdom                                                    |
| VR     | Virtual Reality                                                   |
| VRM    | Vertical Roller Mill                                              |
| VSM    | Value Stream Mapping                                              |
| WCED   | World Commission on Environment and Development                   |
| WHR    | Waste Heat Recovery                                               |

# 1 Introduction

## 1.1 Background and Context

The manufacturing industry, with a global output of around 50 trillion USD, is recognised for its crucial role in economic development, job creation, and technological progress [1]. Conversely, ongoing awareness of the sector's negative impacts has affected its sustainability status. Moreover, intense competition has imposed the need to adapt to a rapidly evolving business environment.

At the centre of the manufacturing sector, and human development for that matter, are the Foundation Industries (FIs), which include key materials sectors such as metals, cement, paper, ceramics, chemicals, and glass. Closely aligned with what are commonly termed 'heavy industries', 'basic materials', or 'process industries', these sectors supply essential inputs across the economy and underpin downstream industrial value chains. However, they are also among the most energy- and carbon-intensive sectors, responsible for nearly 20% of global industrial CO<sub>2</sub> emissions [2]. As regulatory, market, and societal pressures to meet net-zero targets grow, the journey toward decarbonisation and improved resource efficiency in these sectors remains particularly challenging.

Improving sustainability in these sectors requires interventions not only at the organisational or sectoral level but also at the manufacturing process level, where most resource and energy consumption occurs. Understanding and optimising these unit processes is critical for enabling meaningful performance improvements and targeted interventions. Decision-making and benchmarking tools are therefore vital for enabling performance improvements at the process level. Yet, existing methods often lack the flexibility, granularity and cross-sector comparability required to address emerging sustainability demands. This research addresses these challenges by conducting in-depth studies of manufacturing processes and developing frameworks and guidelines to support sustainability-driven decision-making, benchmarking and process improvement within and across industrial sectors. In essence, the process level is proposed as

a *tertium comparationis* (a common basis of comparison) that enables inclusive benchmarking across sectors based on shared functions rather than sectoral boundaries. The following sections outline the background, scope, research aim and objectives, and structure of the thesis.

### **1.1.1 The Role of Foundation Industries**

Foundation industries refer to a group of energy- and resource-intensive sectors that form the bedrock of industrial economies. These typically include cement, glass, ceramics, metals, paper and chemicals. They are characterised by high-volume production, continuous or batch processing operations, and essential contributions to the supply chains of virtually all manufacturing and construction activities.

In the UK and globally, foundation industries play a strategically significant role. They collectively support over 75% of all goods manufacturing and underpin infrastructure, transport, defence, and housing sectors [3]. In the UK alone, these industries contribute billions to the economy and support hundreds of thousands of jobs, both directly and indirectly [3]. They are deeply interwoven with wider industrial systems. Their outputs serve as intermediate products used across diverse sectors, meaning any efficiency improvements or sustainability transitions within foundation industries can have cascading effects throughout the economy. Moreover, their reliance on cross-sectoral inputs such as energy, raw materials, and logistics infrastructure makes them central to achieving national and international climate goals, resource security and industrial resilience [4].

### **1.1.2 Sustainability Challenges in Foundation Industries**

Despite their established position within industrial supply chains, foundation industries face acute sustainability challenges driven by their operational characteristics and environmental impacts. Their production processes are inherently energy-intensive, often reliant on high-temperature heat derived from fossil fuels. In addition to direct fuel combustion, several processes also emit carbon dioxide through unavoidable chemical reactions [5].

As a result, foundation industries exhibit a high emissions intensity relative to their economic contribution. For example, while these sectors account for only around 2.5% of the UK's Gross Domestic Product (GDP), they are responsible for approximately 10% of the nation's CO<sub>2</sub> emissions [2].

In recent years, policy and regulatory frameworks have placed increasing pressure on these sectors to reduce their environmental footprint. National net-zero commitments, the UK Emissions Trading Scheme (UK ETS), and the implementation of carbon pricing mechanisms such as the EU Carbon Border Adjustment Mechanism (CBAM) are accelerating the need for deep transformation [6]. At the same time, industry stakeholders are responding to growing demand for sustainability disclosures, low-carbon materials, and responsible sourcing from downstream markets and consumers [7].

However, multiple constraints limit the pace of transition. Many facilities still rely on legacy infrastructure with limited flexibility to accommodate emerging low-carbon technologies or circular economy principles [8]. High capital intensity, long asset lifetimes and quality assurance requirements further complicate the adoption of alternative production routes. Moreover, the integration of secondary materials and process electrification remains limited in practice, particularly in applications with strict performance specifications [8].

To overcome these systemic bottlenecks, there is an urgent need for robust, data-driven strategies that support sustainability improvements at the process level. These must go beyond high-level targets to provide actionable insights into process performance, material flows and emissions hotspots. Decision-making tools that incorporate benchmarking and cross-sector learning can help these industries navigate the complex trade-offs between operational efficiency, cost, and carbon reduction.

### **1.1.3 Benchmarking, Decision-Making, and Process Improvement**

Effective decision-making is essential for improving manufacturing performance, particularly in energy- and emission-intensive sectors where operational changes can yield substantial environmental and economic benefits. In recent decades,

various decision-support tools have emerged to aid manufacturers in evaluating alternatives, prioritising investments, and managing process trade-offs. These include life cycle assessment (LCA), multi-criteria decision analysis (MCDA), simulation models, and key performance indicator (KPI) frameworks, among others [9].

A central component of decision-making in industrial settings is benchmarking, which refers to the process of evaluating the performance of a process, product, or facility against defined standards or peer references [10]. Benchmarking helps identify inefficiencies, define performance thresholds, and set realistic targets for improvement. In the context of foundation industries, benchmarking is particularly relevant for evaluating process performance across a range of sustainability metrics, including energy consumption, emissions, material efficiency, operational costs and production quality. It also facilitates technology selection, process optimisation, and performance tracking over time.

However, existing benchmarking and decision-making tools often face limitations in their applicability to complex, diverse industrial settings. Many tools are designed for specific sectors, technologies, or geographical regions, limiting their ability to support cross-sector comparisons or adapt to new contexts [11]. Furthermore, process-level granularity is frequently lacking. Tools tend to focus on facility-level or product-level data, making it difficult to assess and improve discrete process units.

In addition, most established approaches do not fully integrate multifaceted sustainability metrics into the decision-making process. While environmental indicators such as energy use, emissions and material flows are commonly included, social and economic dimensions of sustainability are often overlooked or inconsistently applied [12]. This presents a barrier to holistic performance evaluation and slows progress toward integrated sustainability goals.

To address these challenges, there is a growing need for adaptable, process-focused decision-making frameworks that incorporate robust benchmarking methods and sustainability metrics [13, 14]. Such tools should enable multi-criteria analysis that can account for environmental, economic and social

objectives simultaneously. By incorporating similarity analysis at the process level, this research enables granular, cross-sector comparisons that support sustainability benchmarking. This approach can support more informed, data-driven decisions by facilitating the identification of improvement opportunities within individual sectors and the discovery of transferable interventions that can be shared across sectors.

## **1.2 Research Gaps**

Although progress has been made in sustainability benchmarking and decision-support tools, key limitations remain for their use at the process level in foundation industries.

Most existing approaches operate at the facility or product level, offering limited insight into unit operations where many impactful interventions occur. Tools are often sector-specific, preventing cross-industry comparisons and limiting the transfer of best practices. The selection and use of sustainability KPIs also remain inconsistent, with little standardisation or guidance on relevance at the process level. Furthermore, many methods depend on subjective inputs, reducing transparency and reproducibility. At the same time, foundation industries face growing pressure to improve performance and align with net-zero targets. There is a need for process-focused, cross-sectoral frameworks that support data-driven decision-making, enable consistent benchmarking, and highlight shared improvement opportunities.

## **1.3 Aim, Objectives, and Research Questions**

This thesis aims to conduct a comprehensive assessment of manufacturing processes within the Foundation Industries and to develop a framework for evaluating similarities among processes both within and across. This framework is intended to support the establishment of multi-sector benchmarking strategies, identify shared improvement opportunities and enable cross-sectoral innovation pathways.

The research objectives have been formulated to support this overarching aim. Each objective has been designed to be specific, measurable, attainable and

aligned with the central research goal, thereby ensuring clear direction and sustained progress throughout the study. The defined objectives are as follows:

1. To investigate existing decision-making approaches and methods, identifying key challenges for their implementation and lacking aspects in their applicability.
2. To facilitate the definition of environmental KPIs that drive sustainability transitions and continuous improvements in manufacturing operations
3. To enhance process-level efficiency by evaluating intensive processes, identifying resource optimisation opportunities and proposing actionable benchmarking approaches.
4. To identify shared characteristics and improvement opportunities across manufacturing processes, enabling cross-sectoral learning and collaboration.
5. To enable cross-industry benchmarking and informed decision-making by integrating sustainability metrics into a similarity-based approach.

## **1.4 Methodological Approach and Research Scope**

This study undertakes a comprehensive investigation into sustainability-driven decision-making and benchmarking within manufacturing, addressing the research gaps and industrial needs. As illustrated in Figure 1, the research is structured around a clear flow from foundational inputs to targeted research activities and final outputs. A central aspect of this study is the focus on foundation industries and their role in broader sustainability transitions, with particular emphasis on the environmental dimension.

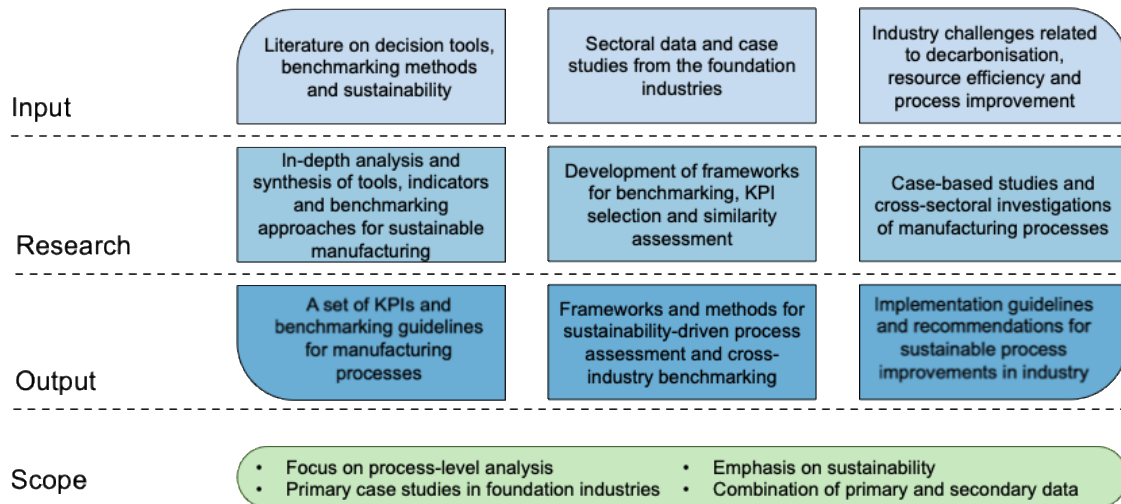


**Figure 1 Methodological Approach Overview**

Within the context of sustainable manufacturing, this research begins with a structured collection of literature covering the use of decision-making and benchmarking tools to support sustainable performance improvement. This is achieved by conducting a comprehensive exploration of the literature on decision-making methods, sustainability frameworks, environmental KPIs, and process-level benchmarking approaches. This theoretical foundation is complemented by sector-specific data and case studies, primarily drawn from the foundation industries, providing insight into current practices in energy and emissions management. In parallel, challenges linked to decarbonisation and resource efficiency are explored to contextualise industry needs. In terms of data acquisition, the research adopts a hybrid approach that integrates both primary and secondary data, ensuring a balance of rigour and relevance across its analytical, developmental and use phases. These inputs form the empirical and conceptual base of the research.

The core research activities encompass three interconnected strands. The first involves an evaluation and synthesis of existing tools and indicators used in sustainable manufacturing, aimed at identifying their capabilities and limitations as well as the energy and resource-intensive processes inherent to the foundation industries. The second strand focuses on the development of new frameworks that integrate validated KPIs, benchmarking criteria, and a similarity-based approach for assessing manufacturing processes across sectors. These

frameworks are designed to enable process-level analysis while remaining adaptable to varying industrial contexts. The third component of the research adopts a case-based perspective, applying the developed tools to industrial scenarios.

The research outputs are organised around three primary deliverables. First, a set of KPIs and benchmarking guidelines is produced, tailored to the operational realities of manufacturing processes. Second, the study presents novel frameworks for sustainability-driven process assessment and cross-industry benchmarking, underpinned by a similarity-based methodology. Finally, implementation guidelines are developed, offering practical recommendations to support industry uptake and inform decision-making around sustainable process improvement. These contributions are disseminated through peer-reviewed publications and supported by case studies that demonstrate their applicability in diverse manufacturing contexts.

The overarching scope of this research is grounded in a process-level analytical focus, with primary applications in the foundation industries. However, the tools and frameworks developed are expected to be transferable to other manufacturing sectors.

## **1.5 Research Contributions and Publication-Based Thesis Structure**

This thesis adopts a publication-based format, with each chapter representing an objective which is underpinned by one or more peer-reviewed journal or conference papers. The work contributes to the field of sustainable manufacturing through the synthesis of previous work, the introduction of new benchmarking and similarity-based frameworks, and the generation of cross-sectoral insights relevant to energy-intensive industries. These contributions address key challenges identified in the literature, including the need for improved decision-making at the process level, the integration of sustainability metrics, and the transferability of improvement strategies across sectors. Figure 2 illustrates how the chapters, objectives, and publications are interlinked. Each research

objective is aligned with one or more publications, and each chapter builds upon the previous one to form a coherent narrative.

|                          |                                                                                                                                                                                                                                       |                                                                                                                                      |                                                                                                                                                             |
|--------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Chapter 2<br>Objective 1 | <b>Paper 1.</b> A Review of Comparative Decision Tools for Process Selection and Performance Improvement in Manufacturing                                                                                                             |                                                                                                                                      | Z. Sherif and K. Salontis, J. Manuf. Process., 2024                                                                                                         |
|                          | <b>Approaches</b> <ul style="list-style-type: none"> <li>Systematic review of decision-making tools</li> <li>Analysis of challenges in tool implementation</li> </ul>                                                                 | <b>Outcomes</b> <ul style="list-style-type: none"> <li>Identification of gaps</li> <li>Tool implementation roadmap</li> </ul>        |                                                                                                                                                             |
| Chapter 3<br>Objective 2 | <b>Paper 2.</b> Energy Benchmarking of Manufacturing Processes in Foundation Industries<br><b>Paper 3.</b> Identification of the Right Environmental KPIs for Manufacturing Operations: Towards a Continuous Sustainability Framework |                                                                                                                                      | S. Sarfraz, Z. Sherif, M. Jolly, and K. Salontis, Procedia CIRP, 2023.<br>Z. Sherif, S. Sarfraz, M. Jolly, and K. Salontis, Materials, 2022.                |
|                          | <b>Approaches</b> <ul style="list-style-type: none"> <li>Examination of KPI utilisation and effectiveness</li> <li>Development of KPI selection framework</li> </ul>                                                                  | <b>Outcomes</b> <ul style="list-style-type: none"> <li>KPI deployment challenges</li> <li>KPIs selection framework</li> </ul>        |                                                                                                                                                             |
| Chapter 4<br>Objective 3 | <b>Paper 4.</b> Investigating Energy Consumption Drivers and Reduction Measures in Key Manufacturing Sectors<br><b>Paper 5.</b> Benchmarking of Energy Consumption and CO2 Emissions in Cement Production – A Case Study              |                                                                                                                                      | Z. Sherif, S. Sarfraz, M. Jolly, and K. Salontis, Int. J. Sustain. Eng., 2025.<br>S. Sarfraz, Z. Sherif, M. Jolly, and K. Salontis, in TMS 2024, pp. 35–46. |
|                          | <b>Approaches</b> <ul style="list-style-type: none"> <li>Evaluation of high-impact processes</li> <li>Benchmarking energy and emissions</li> </ul>                                                                                    | <b>Outcomes</b> <ul style="list-style-type: none"> <li>Manufacturing process maps</li> <li>Benchmarking approach</li> </ul>          |                                                                                                                                                             |
| Chapter 5<br>Objective 4 | <b>Paper 6.</b> Greening Foundation Industries: Shared Processes and Sustainable Pathways                                                                                                                                             |                                                                                                                                      | Z. Sherif, S. Sarfraz, M. Jolly, and K. Salontis, Sustainability, 2023.                                                                                     |
|                          | <b>Approaches</b> <ul style="list-style-type: none"> <li>Comparison of shared processes across sectors</li> <li>Identification of improvement pathways</li> </ul>                                                                     | <b>Outcomes</b> <ul style="list-style-type: none"> <li>Commonality framework</li> <li>Cross-sectoral recommendations</li> </ul>      |                                                                                                                                                             |
| Chapter 6<br>Objective 5 | <b>Paper 7.</b> A Multi-Criteria Similarity-Based Framework for Sustainability Assessment of Manufacturing Processes in Foundation Industries                                                                                         |                                                                                                                                      | Z. Sherif and K. Salontis, J. Manuf. Process., 2025.                                                                                                        |
|                          | <b>Approaches</b> <ul style="list-style-type: none"> <li>Establishment of</li> <li>Development of a similarity-based benchmarking framework</li> </ul>                                                                                | <b>Outcomes</b> <ul style="list-style-type: none"> <li>Cross-sectoral benchmarking approach</li> <li>Similarity framework</li> </ul> |                                                                                                                                                             |

**Figure 2 Linkage between Thesis Chapters, Research Objectives and Associated Publications**

A comprehensive review was conducted as part of Chapter 2, addressing Objective 1 of the thesis. This review, titled “*A Systematic Review of Process-Level Comparative Decision-Making Methods in Manufacturing*”, followed PRISMA guidelines and applied predefined inclusion and exclusion criteria to evaluate process-level decision-making tools in manufacturing. A total of 37 studies were analysed using NVivo, with a focus on their effectiveness, limitations, and cross-sector applicability. The review highlighted key gaps, including limited scalability, weak integration of sustainability metrics, and insufficient implementation guidance. These findings led to the development of a hybrid roadmap to support more effective adoption of decision-support tools in industrial settings.

Chapter 3 responds to Objective 2 and is composed of two interrelated studies. The first, presented as a conference paper in *Procedia CIRP* under the title “*Energy Benchmarking of Manufacturing Processes in Foundation Industries*”,

explored discrepancies in energy metrics used across foundation industry sectors. Through survey-based analysis, the study evaluated the metrics based on criteria such as accuracy, data collection and trackability. Insights from this work informed the development of a structured framework for environmental KPI identification and selection, which was later published in *Materials MDPI* as *“Identification of the Right Environmental KPIs for Manufacturing Operations”*. The resulting framework features a curated KPI database, categorisation by impact area, prioritisation aligned with sustainability objectives, and validation through expert consultation. Together, these two papers address the fragmented and inconsistent use of environmental indicators while supporting continuous sustainability improvement in manufacturing operations.

In Chapter 4, linked to Objective 3, the thesis shifts to process mapping and benchmarking. The first study, titled *“Investigating Energy Consumption Drivers and Reduction Measures in Key Manufacturing Sectors”*, maps energy flows and emissions across main processes in the foundation industries. Causal loop diagrams are used to analyse interdependencies among energy-influencing factors, offering a systems-level view of performance drivers. This is complemented by a threshold analysis that benchmarks current industrial practices against best available technologies (BATs), research-driven innovations, and theoretical minimums. Together, the mapping, factor analysis, and benchmarking reveal process-level inefficiencies, highlight sector-specific constraints, and inform targeted strategies for performance improvement. Building on this foundation, a second study, presented at the TMS Annual Meeting and titled *“Benchmarking of Energy Consumption and CO<sub>2</sub> Emissions in Cement Production”*, develops a sector-specific benchmarking methodology. Using a 2850-tonne/day cement plant as a case study, it reveals substantial efficiency gaps and evaluates the impact of BAT, such as vertical roller mills and Organic Rankine Cycle systems, with energy intensity reduction potentials of up to 51% for clinkerisation and 30% for grinding.

Objective 4 is addressed in Chapter 5, which focuses on identifying cross-sectoral improvement opportunities through shared process analysis. This work,

published in *Sustainability MDPI* as “*Greening Foundation Industries: Shared Processes and Sustainable Pathways*”, adapts the Dependency Structure Matrix (DSM) to identify 18 shared processes across foundation industries, including pyroprocessing and milling. These processes are analysed by their principle, outcome and equipment used to uncover opportunities for coordinated abatement strategies. The analysis highlights cross-sector solutions, such as heat recovery and electrification, demonstrating the potential for knowledge transfer between sectors and accelerating sustainability transitions by leveraging shared improvements.

Chapter 6 addresses Objective 5 by introducing a novel framework for similarity-based benchmarking. This framework enables a comparative assessment of manufacturing processes within and across sectors, integrating sustainability metrics with performance similarity analysis. The associated study, titled “*A multi-criteria similarity-based framework for sustainability assessment of manufacturing processes in foundation industries*”, proposes a methodology that supports data-driven process improvement at scale.

Chapter 7 consolidates the findings from across the thesis, aligning them with the research aims and objectives. It discusses how each chapter contributes to advancing process-level sustainability benchmarking and highlights the progression from indicator development and systems analysis to cross-sector process mapping and the final benchmarking framework. It also outlines key limitations and proposes directions for future research. Together, these elements demonstrate how the thesis delivers a cohesive and practical response to the challenges of sustainability assessment in foundation industries.

The thesis concludes with a summary of the major findings that addressed all proposed objectives. The logical structure of the thesis mirrors the research progression, beginning with a literature review, advancing through KPI development and benchmarking methods, and culminating in a similarity-based framework. Each chapter builds on the insights of the previous one, ensuring coherence across the research journey. Together, these chapters and publications form a cohesive body of work that not only contributes to academic

knowledge but also provides actionable tools and guidance for industry stakeholders seeking to implement sustainable, process-level improvement strategies. It is important to note that the structure and formatting of the published papers have been adapted within this thesis to ensure consistency, improve readability, and support a unified narrative across chapters.

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## **2 A review of comparative decision tools for process selection and performance improvement in manufacturing <sup>1</sup>**

### **2.1 Paper Linkage to Research Aim and Objectives**

This chapter aligns with Objective 1 of the thesis which was to investigate existing decision-making approaches and methods, identifying key challenges for their implementation and lacking aspects in their applicability. It provides a foundational, cross-sectoral assessment of decision-making tools used at the manufacturing process level, particularly those aimed at enabling comparative evaluations.

The rationale behind this study stems from the increasing complexity in modern manufacturing and the corresponding expansion of decision-making tools. Despite a growing body of research, existing methods are often fragmented, lack scalability and are rarely tailored to process-level decisions. This review was therefore conducted to map the approaches, classify their core methods and impact areas, and highlight their strengths and shortcomings. It uniquely focuses on process-level decisions, with an emphasis on comparative analysis, and synthesises the current state of research across a broad industrial base using PRISMA-guided systematic review methodology and NVivo-based thematic coding.

By identifying methodological and implementation-related gaps, this paper sets the stage for the development of new, hybrid frameworks and toolkits that are addressed in subsequent chapters.

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<sup>1</sup> Z. Sherif and K. Salonitis, "A review of comparative decision tools for process selection and performance improvement in manufacturing," 2025 (To be submitted).

## 2.2 Introduction

Manufacturing is a cornerstone of modern economies, driving technological advancements, economic growth and societal development. At its core, manufacturing encompasses a plethora of processes, systems and strategies that collectively contribute to producing goods and services. It is responsible for US\$35tn of output in 2024 globally with 5.46m enterprises [1]. The complexity of manufacturing systems, comprising products, equipment, personnel, information and control mechanisms, necessitates robust tools and methods to ensure efficiency, sustainability and competitiveness in the global market [2,3].

The importance of manufacturing processes cannot be overstated, as they form the foundation of production systems, influencing product quality, cost-efficiency and environmental impact. Manufacturing processes are not just isolated operations but integral components of larger systems that must be optimised to meet market demands and regulatory standards. For example, machining a metal component for an automotive engine involves precision cutting and shaping to achieve the required tolerances and surface finish. This single-unit process directly impacts the engine's performance and longevity, as well as the overall manufacturing cost and environmental footprint. At the same time, the adoption of advanced 4.0 technology, such as artificial intelligence, robotics and the Internet of Things (IoT), has the potential to improve overall efficiency and productivity while reducing costs. However, leveraging these technologies adds complexity to operating and optimising such processes [4].

Therefore, decision-making at the unit process level, such as selecting between machining or casting for a specific component, plays a critical role in determining the overall success of manufacturing systems. Given the multifaceted nature of manufacturing, decision-makers are often confronted with complex challenges that require careful consideration of multiple factors. These factors include cost, quality and sustainability [5]. While heuristics and rules of thumb are often used for decision-making in manufacturing due to their simplicity and ease of application, they fall short in addressing the growing complexity of modern manufacturing systems. These methods lack the ability to systematically analyse

trade-offs between conflicting factors and are prone to subjective biases. In contrast, structured decision-making tools provide a robust, data-driven approach, enabling manufacturers to handle the intricate interdependencies of their operations and optimise processes with greater accuracy and scalability. To navigate these challenges, various decision-making tools and approaches have been developed. These tools are established through the support of a variety of techniques ranging from benchmarking and monitoring methods [6,7] to multi-criteria decision analysis (MCDA) [8,9] and the increasingly widespread use of artificial intelligence (AI) [10,11], each offering unique advantages and limitations depending on the context of their application.

Decision-making tools are particularly vital at the process level, where detailed analysis of specific manufacturing processes can significantly improve efficiency and sustainability [12]. Furthermore, comparing processes is paramount, enabling a more informed evaluation of different methods, practices and standards. Comparative analysis allows for a nuanced understanding of how various processes perform under similar or differing conditions, making it possible to identify the most suitable possibility for given requirements [13–15]. This analysis also serves as the foundation for performance evaluation by establishing benchmarks and competitive priorities [16].

Such decision-making is especially important in manufacturing, where decisions often need to be made regarding which processes to implement or enhance based on multiple, and sometimes conflicting, factors. This study systematically reviews decision-making concepts and approaches targeting unit manufacturing processes. The review aims to explore the tools available for process-level decision-making, including those with broader implications for system-level decisions. The primary focus is on methods involving comparative evaluation. By doing so, this study seeks to uncover strategies that evaluate individual processes and provide a broader understanding of how these processes perform relative to one another. The scope of this review is intentionally broad, encompassing diverse industries and manufacturing contexts, to identify common trends, gaps in the literature and opportunities for further research.

The findings of this study can guide manufacturers, researchers and policymakers in selecting and implementing effective decision-making tools to optimise production processes. By providing a comprehensive overview of comparative methods, the study also highlights areas for innovation and encourages the development of tailored tools for specific manufacturing needs.

## **2.3 Literature review**

### **2.3.1 Decision-Making Tools in Manufacturing**

Decision-making tools are crucial for optimising and improving manufacturing processes. These tools offer structured methods for evaluating multiple factors, such as cost, quality, sustainability, and efficiency, which are essential for driving improvements in manufacturing operations [17,18]. Over time, various approaches have been developed to aid decision-makers in balancing trade-offs and selecting the best strategies in complex industrial settings.

These tools provide a means of systematically assessing processes and making informed decisions across different operational levels, from individual production processes to broader system-wide evaluations. Depending on the operational focus, the impacts of these tools can vary from direct improvements in production at the process level [19] to more comprehensive gains in sustainability or resource optimisation when applied at the system or organisational level [20]. Their procedure may range from qualitative methods to more data-driven, quantitative models, helping manufacturers assess both current operations and future scenarios. By applying decision-making tools at different levels of manufacturing, companies can address specific operational challenges while improving overall production efficiency and strategic alignment [21,22]. The adoption and integration of such tools have led to notable advancements in numerous operating aspects across various industries [23,24]. However, challenges remain, particularly in ensuring data availability, managing complexity, and adapting tools to new technologies and manufacturing contexts [25,26].

### **2.3.2 Analysis of Manufacturing Processes**

Analysing manufacturing processes is essential for identifying inefficiencies, optimising resource use and improving overall production quality. This analysis often includes evaluating different processing levels, from individual processes to entire production systems. The focus can be exclusively on particular processes. Still, it can also adopt a bottom-up approach where improvements at the process level trickle upwards, ultimately impacting the entire production system or facility [27]. Various methodologies are employed to achieve these goals, each focusing on different aspects of the manufacturing process [28].

The need for thorough and systematic process evaluation has driven the development of more advanced methods for capturing the complexity of modern manufacturing systems. As new challenges arise, such as shifts toward more sustainable or digital manufacturing practices, further research and innovation in process analysis will be needed to address these evolving requirements [29,30].

### **2.3.3 Previous related work**

Several review studies have explored various decision-making tools and methods within different manufacturing contexts, offering insights into their applications, benefits and limitations. For instance, Ng et al. [31] focused on the application of machine learning (ML) tools in additive manufacturing, particularly in areas such as quality control, process optimisation and material formulation. This review provided a comprehensive analysis of how machine learning enhances these aspects within the additive manufacturing sector, highlighting the strengths and the areas where further research is needed. In parallel, a study by Mallioris et al. [32] on predictive maintenance applications across diverse manufacturing sectors discovered a high dependence on ML approaches to predictive maintenance across various sectors.

In a more expansive context, several reviews have explored the application of AI in manufacturing. Elahi et al. [33] examined the implementation of AI techniques throughout the lifecycle of industrial equipment, from design to recycling, emphasising the role of AI in optimising process control and decision-making

across the major phases of an industrial equipment lifecycle. Similarly, Hoffmann and Reich [34] specifically assessed the use of AI in visual quality control for defect detection, identifying gaps in current research, particularly the limited use of AI in explaining decision-making processes in quality assurance.

Other reviews concentrated on the various selection and optimisation techniques included under the umbrella of MCDA tools. For instance, a study by Raja and Rajan [35] explored utilising MCDA modelling in additive manufacturing, mainly focusing on polymer technology. They explored the challenges and opportunities presented by these methods, underscoring their importance in overcoming specific optimisation issues. Similarly, a review by Jamwal et al. [36] examined the use of MCDA techniques in sustainable manufacturing, offering insights into how these tools support decision-making processes to achieve sustainability goals within various manufacturing sectors. The application ranged from material selection to scheduling to identifying factors and drivers of sustainable manufacturing.

Broad reviews have also been conducted on target monitoring approaches. For instance, Ravelomanantsoa et al. [37] explored approaches devoted to the design and implementation of performance measurement systems for production functions spanning supply, manufacturing, and distribution. They aspired to aid companies and consultants in choosing the most appropriate approach based on the availability and depth of performance indicators.

Lastly, studies have focused on integrating advanced technologies in manufacturing decision-making. For instance, Inturi et al. [38] review of digital twins in transmission and industrial machinery provided a detailed analysis of their definitions, applications, and performance in enhancing manufacturing and lifecycle management. Similarly, Wu and Liang [39] investigated intelligent data acquisition and presentation methods in manufacturing, emphasising the integration of process knowledge, management, and decision-making to enhance operational efficiency. Likewise, Sekaran et al. [40] explored the application of virtual reality (VR) in digital factory simulations. These illustrate how VR aids in the efficient operation of manufacturing facilities. These studies have provided

unique insights into integrating these technologies into manufacturing decision-making. Table 1 compares different surveys presented in the literature in the context of various aspects, i.e. sectoral and tool specificity as well as operational level.

**Table 1 Comparison of existing surveys**

| Ref        | Year | Non-sector specific | Non-tool specific | Process level |
|------------|------|---------------------|-------------------|---------------|
| [31]       | 2024 | x                   | x                 | ✓             |
| [32]       | 2024 | ✓                   | x                 | x             |
| [33]       | 2023 | x                   | x                 | x             |
| [34]       | 2023 | x                   | x                 | x             |
| [35]       | 2023 | x                   | x                 | ✓             |
| [36]       | 2020 | ✓                   | x                 | ✓             |
| [37]       | 2017 | ✓                   | x                 | x             |
| [38]       | 2024 | x                   | x                 | ✓             |
| [39]       | 2024 | ✓                   | x                 | x             |
| [40]       | 2021 | ✓                   | x                 | ✓             |
| This study | 2024 | ✓                   | ✓                 | ✓             |

### 2.3.4 Identified Research Gaps

While these reviews provide valuable insights into specific tools, techniques, and industries, there is a noticeable gap in the literature concerning a comprehensive review that considers the full spectrum of decision-making tools at the manufacturing process level that incorporate comparative analysis. This gap underscores the need for a holistic review that highlights the strengths and limitations of existing tools and identifies areas where current methods may fall short, particularly in terms of their applicability to different industries or manufacturing aspects. By emphasising tools that facilitate comparisons, whether across various processes, industries or within the same sector, this review aims to fill that gap. Such a focus is essential for advancing the field, as it enables more nuanced and informed decision-making, ultimately guiding future research and informing practical decisions in the industry.

### 2.3.5 Research Questions

Based on the scope and focus of the review, the following research questions have been formulated:

1. What decision-making methods and approaches are currently used at the process level in manufacturing, and how do they vary in their application?
2. What are the key impacts and limitations of existing decision-making methods, and how can these be addressed in future research?
3. How can these methods be integrated into manufacturing systems to support effectiveness and scalability?

## 2.4 Methodology

This study employed a systematic literature review (SLR) to provide a comprehensive overview of decision-making tools at the manufacturing process level. It focused on comparative analysis across or within different sectors.

Figure 3 highlights the growing academic interest in decision-making tools for manufacturing. Over the past decade, the number of publications has increased steadily, reflecting a heightened focus on improving process efficiency and optimisation by utilising various tools and approaches.

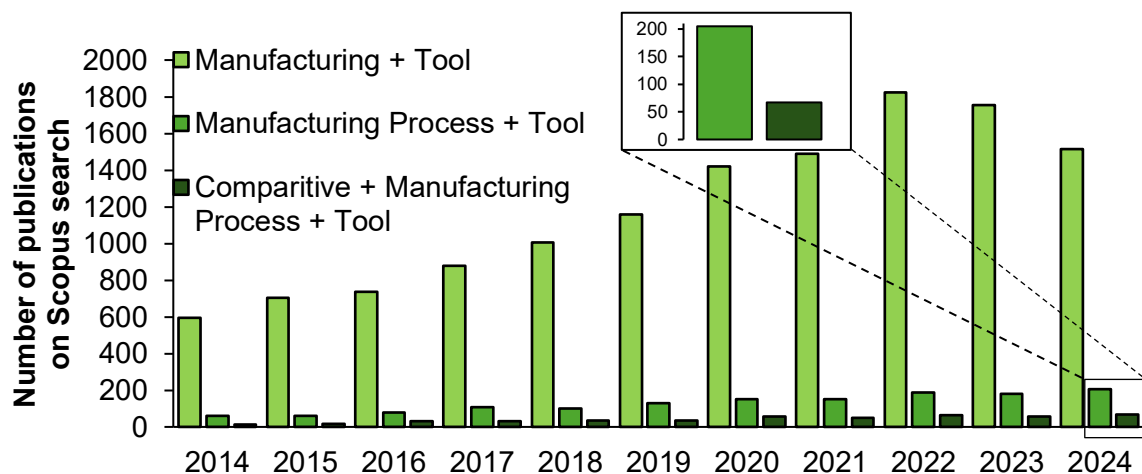


**Figure 3. From 2014 to 2024, the number of articles retrieved from Scopus showed progressive keyword inclusion. It displays the keyword search results**

**for 'Comparative Manufacturing Process Decision Tools', 'Manufacturing Process Decision Tools' and 'Manufacturing Decision Tools'.**

Initial search queries using broad terms and synonyms like “manufacturing decision tools” demonstrated a general interest, yielding around 13,000 articles. However, when refining the search to focus on analyses between processes, the number of relevant publications narrowed to approximately 1,400 studies. Incorporating terms like “Comparative” has further reduced the results to 500 studies. This significant reduction points to the specialised nature of research in comparative decision-making at the manufacturing process level, but also underscores its growing relevance within the academic community.

This trend not only signals an increasing recognition of the importance of comparative analysis in process decision-making but also indicates a shift toward more precise, data-driven evaluations. The analysis revealed that over time, research has increasingly emphasised the importance of comparing different manufacturing processes across and within sectors to identify optimal approaches for production effectiveness. These findings illustrate the broader transition within manufacturing from isolated process enhancement to holistic, comparative assessments aimed at fostering innovation and competitiveness.

Consequently, the systematic review method is ideal for synthesising and evaluating existing research. It allows for identifying knowledge gaps and provides robust insights that can inform future studies on decision-making tools for manufacturing processes. The PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines ensure transparency, accuracy, and comprehensiveness throughout the review process [41]. It offers a 27-item checklist and a flow diagram that guides this review's identification, screening, and inclusion phases, ensuring a clear and structured approach to reporting findings.

#### **2.4.1 Search Strategy and Databases**

This review identified relevant literature using two primary databases: Scopus and Web of Science. These databases were selected because they cover a broad

range of peer-reviewed manufacturing and decision-making research studies, making them highly suitable for this review.

Keywords and Boolean operators such as "manufacturing process", "decision tools", and "comparative analysis" were combined to retrieve a comprehensive list of studies. Wildcards and synonyms were employed to capture variations of search terms, ensuring a broad yet focused set of results. The results were limited to publication dates (from 2010 onwards), peer-reviewed articles and studies written in English. This strategy aligned directly with the study's objectives, enabling the identification of robust, process-level decision-making tools within manufacturing. By focusing on recent advancements and employing comparative analysis, the review ensures that established and emerging methods are captured, providing insights across multiple sectors.

To avoid reviewing duplicated papers, the entire lists of papers that appeared for each of the searching criteria in the two databases were exported to Zotero to be compared, and 347 duplicates were removed. The total number of records screened was 494. In addition to the systematically reviewed studies, 10 previous review papers were analysed to assess existing research gaps and validate the novelty of this study's focus. Furthermore, 72 additional references were used to provide context, theoretical background and discussion support for the identified decision-making tools. While these supplementary references were not part of the systematic selection process, they were essential for comparative analysis and broader sectoral insights. A complete overview of the search terms and the updated PRISMA flowchart is displayed in Figure 4.

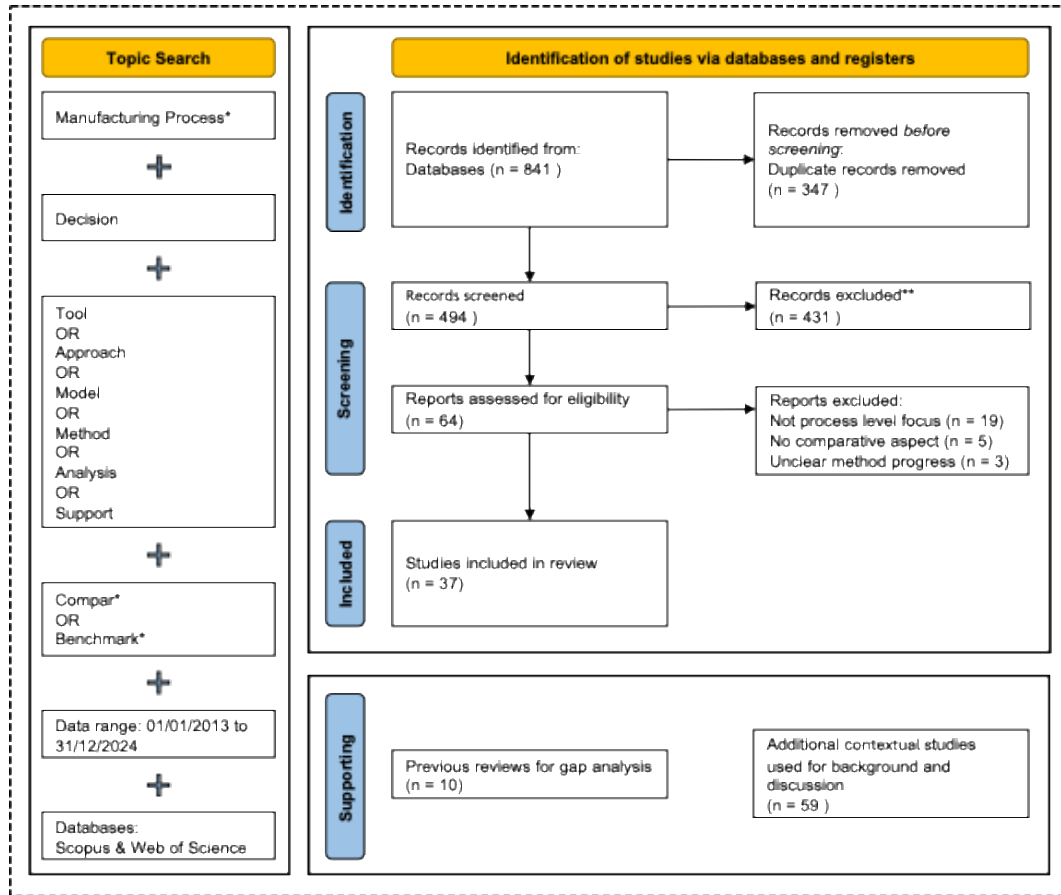


**Figure 4 PRISMA Flowchart alongside search terms and scope, including systematically reviewed studies (n=37), previous reviews for gap analysis (n=10), and additional references for context and discussion (n=59)**

## 2.4.2 Study Screening and Selection Criteria

Once the relevant studies were identified, a two-stage screening process was employed to ensure the inclusion of studies most appropriate to the research objective. Studies were considered if they employed cross-sector comparative analysis methods of manufacturing processes. Conversely, studies focusing solely on single-process optimisation without comparison, i.e. production parameter optimisation or those irrelevant to the manufacturing functions, were excluded.

The first phase involved screening titles and abstracts against these criteria. This effectively eliminated a large portion of irrelevant material, with 431 records removed during this stage. The remaining 64 studies were then sought for

retrieval for further review. In the second phase, the full text of these studies was thoroughly reviewed using the same inclusion criteria. At this stage, additional emphasis was placed on ensuring that studies demonstrated a clear progression from aim to method to findings, and those lacking sufficient methodological rigour were excluded. This deeper analysis resulted in removing an additional 27 studies, leaving only the most relevant papers that focused explicitly on decision-making tools that incorporate comparative approaches at the manufacturing process level. These two screening phases ensured a refined and focused body of literature directly aligned with the objectives of this research on decision-making tools in the manufacturing sector.

### **2.4.3 Data Extraction, Coding, and Analysis**

The 37 extracted studies [42–78] were analysed using NVivo to facilitate the categorisation of key concepts and identify patterns and thematic trends across the studies. The process began with a systematic data extraction, where crucial information such as the core concept of the decision-making method, the manufacturing process it targeted, and the outcome reported was identified. This ensured consistency and allowed for a structured examination of how these tools were applied across various industrial settings. The coding structure was further developed through an iterative review process, which was used to categorise studies by key themes, such as the tools' effectiveness, drivers of functionality and boundaries. This approach facilitated a deeper understanding of the strengths and limitations of each tool, highlighting recurring patterns that revealed the comparative efficacy of various decision-making methodologies. By integrating the data extraction and coding processes, the method comprehensively evaluated the selected studies, ensuring that key insights and trends were analytically captured.

## **2.5 Findings and discussion**

The findings section aims to provide a comprehensive evaluation of the studies included in this review, highlighting key themes, trends, and gaps. The section will present and discuss an analysis of these studies, exploring the evolution of decision-making tools in manufacturing, as well as their impacts, limitations, and

intersections among various approaches. Additionally, it will identify gaps in the current research landscape, offering insights for future work.

### 2.5.1 Overview of included studies

An overview of the extracted 37 research papers is provided, highlighting trends in publication frequency over time (Articles summarised in Appendix B - Table B.1). As reflected in Figure 5, there has been a noticeable increase in the number of studies published over the last decade. Early contributions were relatively scarce, with only one study appearing in 2014. However, since 2019, there has been a consistent rise, with the highest number of publications recorded between 2020 and 2023, demonstrating growing academic interest in the field. This trend suggests a heightened focus on decision-making tools in manufacturing, likely driven by the increasing complexity of industrial processes and the demand for more efficient and sustainable solutions.

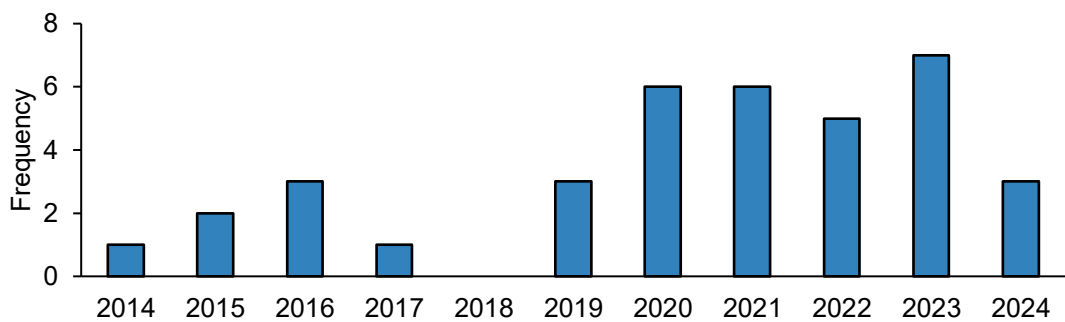


**Figure 5 Frequency of analysed studies on decision-making tools for manufacturing processes from 2014 to 2024**

Further examination of the literature on decision-making tools revealed various overarching themes, each representing significant dimensions of decision-making in manufacturing. The major themes include “Primary Aim”, “Main Method or Concept”, “Industry or Process Group”, “Main Bases of Comparison”, “Impact Area”, “Operational Level”, “Advantages” and “Limitations”. Each theme encompasses multiple subthemes, offering a comprehensive understanding of the specific focal points of each study. Table 2 provides an overview of the final main themes and their descriptions.

**Table 2 Overview of key coding categories**

| Code                      | Description                                                   |
|---------------------------|---------------------------------------------------------------|
| Primary aim               | Main objectives of decision-making tools                      |
| Main method or concept    | Core methods or approaches used in decision-making            |
| Industry or Process Group | Industries or processes where tools are applied               |
| Main bases of comparison  | Key factors for comparing processes or systems                |
| Impact Area               | Areas where tools influence manufacturing outcomes            |
| Operational level         | Levels within manufacturing systems targeted by tools         |
| Impacts and Advantages    | Positive outcomes and benefits of using decision-making tools |
| Limitations               | Challenges and constraints that limit tool effectiveness      |

The thematic map, shown in Figure 6, visually represents the key themes and subthemes identified in the review, illustrating their hierarchical structure and interconnections. This aids in clarifying the breadth and depth of the research focus areas, highlighting how decision-making tools have been applied across various manufacturing contexts.

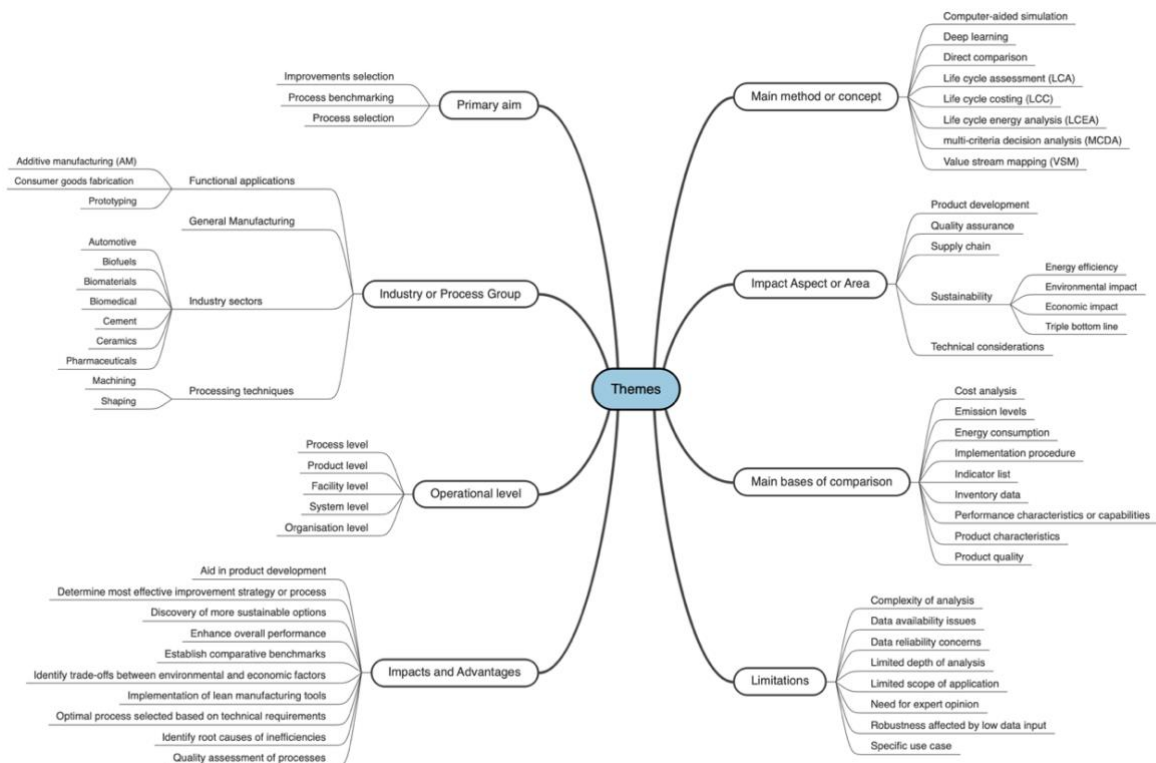


**Figure 6 Themes and sub-themes rising from NVivo coding exercise**

### **2.5.1.1 Sectoral analysis**

The analysed papers covered a broad range of sectors and process groups, with four main categories: generic manufacturing, processing techniques, industrial sectors, and functional applications. Each category reflects different focal points for decision-making tool development and application in manufacturing contexts.

Generic manufacturing refers to research that did not emphasise a specific industry but instead applied general methodologies applicable across multiple sectors. While these studies might not target a single industry, many employed case studies in specific sectors to validate their approaches. This highlights the adaptability and broader applicability of these decision-making tools across various manufacturing contexts. Processing techniques, another significant category, include methods like shaping and machining. These studies often focused on enhancing technical processes and improving production efficiency in areas tied closely to specific processing actions. As these techniques are foundational in many manufacturing industries, tailored data acquisition methods and analysis were necessary for tools to effectively target improvements in these areas. The industrial sectors category includes studies on biomaterials, cement, automotive, and other specialised sectors. These papers tailored their methodologies to meet the technical needs of each industry. Decision-making tools in these studies were developed or adjusted based on sector-specific requirements, such as material characteristics or process constraints, ensuring greater precision in outcomes. The diversity across sectors suggests the importance of customising decision-making tools to align with the unique operational challenges found in each. Lastly, functional applications emerged as the most represented category, particularly in additive manufacturing (AM), which accounts for a significant portion of the research analysed.

Other functional applications include prototyping and consumer goods fabrication. This suggests that decision-making tools targeting functional applications are increasingly being shaped by AM technology advancements, focusing on optimising complex processes and improving outcomes in production efficiency, sustainability, and cost-effectiveness [79]. Furthermore, the

predominance of AM in this analysis points to its growing importance in modern manufacturing strategies and the necessity of robust decision-making tools tailored to these innovative approaches [80]. Figure 7 illustrates the distribution of studies across these functional and process groups, highlighting the growing focus on functional applications, particularly in AM.

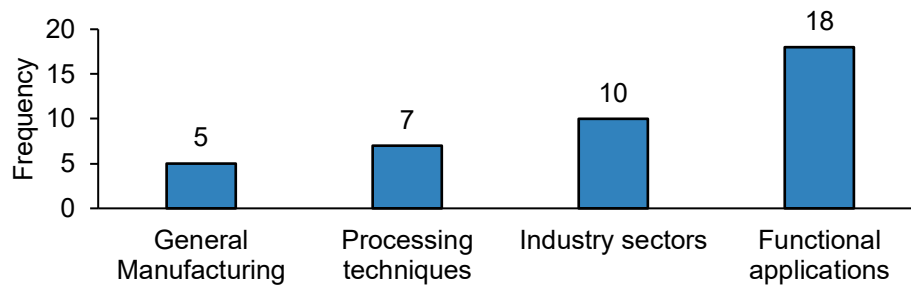


**Figure 7 Distribution of industrial focuses of the analysed literature**

### 2.5.1.2 Analysis of Primary Aims

The analysis revealed three primary aims, namely, process selection, improvement selection and process benchmarking, presented in Figure 8. The most common focus, by far, was process selection, with a frequency of 34 occurrences. This category involves decisions regarding the choice of manufacturing processes for a product, either in development or already developed. It can also encompass the selection of an optimal manufacturing route, considering the range of available processes. The prominence of process selection aligns with the critical nature of early-stage decisions in manufacturing, where selecting the right processes can significantly affect factors like production efficiency, quality, and cost management [81]. Previous studies have underscored the importance of such decisions, suggesting that early-stage process selection plays a vital role in determining overall operational success [82,83].

The next most frequent category, process benchmarking, occurred seven times. This category evaluates and compares existing processes against industry standards or best practices to measure performance. It typically involves setting performance metrics and identifying gaps between current operations and ideal benchmarks. This approach is essential for continuous improvement, allowing

organisations to gauge the efficiency or sustainability of their processes concerning competitors or established standards. By leveraging benchmarking, companies can identify areas for improvement and implement targeted strategies to enhance performance, thus maintaining competitiveness in rapidly evolving manufacturing landscapes. Process benchmarking offers a data-driven method to assess operational success, often forming the foundation for future process optimisations or innovation initiatives [84,85].

Lastly, improvement selection was identified only once, suggesting that it is not a commonly studied area within the scope of these papers. This involves choosing strategies to enhance an existing process or system without completely changing the production method. Improvement selection typically reflects incremental changes aimed at process optimisation rather than total overhauls. This finding resonates with the established focus in the industry on continuous improvement methodologies, such as Lean Manufacturing, which prioritise incremental adjustments for ongoing optimisation [86]. Improvement selection, while less frequent than process selection, is crucial for maintaining competitiveness in industries where small efficiency gains can yield substantial long-term benefits [87].

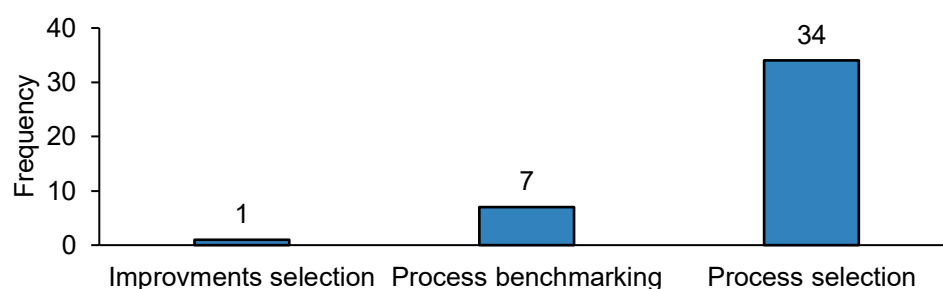


**Figure 8 Primary aims represented by the analysed approaches**

### **2.5.1.3 Analysis of Core Methods and Approaches**

The analysis of the core methods and concepts utilised in the reviewed studies revealed a diverse range of decision-making tools with varying frequencies of use, as displayed in Figure 9. The category with the highest frequency, MCDA, was employed 23 times. MCDA encompasses various techniques to evaluate

multiple conflicting criteria in decision-making scenarios. This category included methodologies such as fuzzy logic, Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and Analytic Hierarchy Process (AHP). Notably, many studies combined these techniques, integrating two or more methods into a singular decision-making framework tailored to specific needs. This reflects the growing recognition of the complexity involved in decision-making processes within manufacturing, where multiple criteria often need to be evaluated simultaneously [88]. Following MCDA, a direct comparison was utilised in 7 studies, representing a straightforward approach where alternatives are compared against each other based on selected requirements. While effective for specific applications, direct comparison may not adequately capture the nuances of complex decision-making scenarios, especially in environments characterised by interdependent factors and dynamic variables.

Life Cycle Assessment (LCA) was used 4 times to evaluate the environmental impacts associated with all the stages of a product's life, from raw material extraction to disposal. This method aligns with the increasing importance of sustainability considerations in manufacturing decisions as industries strive to minimise their ecological footprint [89,90]. However, the relatively low frequency suggests that LCA may still be underutilised compared to other methods, which could present an opportunity for further research and development in this area. Other methods, including computational simulations, Life Cycle Costing (LCC), Life Cycle Energy Assessment (LCEA), and Value Stream Mapping (VSM), were each mentioned only once. This infrequent usage indicates that while these methodologies can offer valuable insights into specific aspects of decision-making, they may not yet be fully integrated into the predominant decision-making frameworks utilised in the sector.

Computational simulations and deep learning were utilised once each, signalling their emerging role in process-level decision-making. Simulations offer the advantage of modelling various manufacturing scenarios, enabling decision-makers to predict and optimise outcomes without physical trials. This makes them particularly useful in dynamic manufacturing environments where real-time

adjustments are critical. While similarly rare in this analysis, deep learning provides powerful predictive capabilities by learning patterns from large datasets, making it well-suited for more complex and data-intensive decision-making tasks. However, both tools have been applied sparingly, likely due to the technical expertise and computational resources required for their effective implementation [91,92]. As these technologies continue to advance and become more accessible, their adoption is expected to increase, especially in sectors where precision and adaptability are essential.

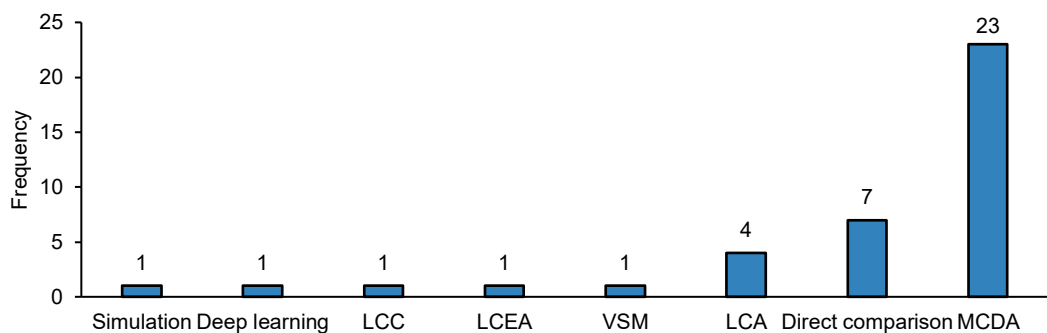


**Figure 9 Tools and approaches employed in the analysed literature**

### 2.5.1.4 Analysis of Impact Areas

The analysis of the targeted aspects in the reviewed studies indicated a clear focus on several key areas within the decision-making frameworks, displayed in Figure 10. Sustainability emerged as the most frequently addressed aspect, appearing in 22 instances. This highlights the growing importance of sustainable practices in manufacturing, where decisions increasingly encompass environmental, economic, and social considerations. The sustainability category predominantly focused on environmental and economic impacts, as well as energy consumption and emissions, reflecting the industry's recognition of the need for a balanced approach to resource utilisation and operational efficiency [93]. Technical considerations were the next most frequent, cited 16 times. This aspect involves examining production capabilities, parameters, and the technical specifications of products. It underscores the critical role that technical factors play in decision-making, particularly in ensuring that processes align with the intended operational outcomes and product requirements. This focus on

technical specifications suggests that industries are prioritising both efficiency and the feasibility and excellence of the manufacturing processes. Quality assurance was addressed in 8 studies, indicating its significance in the decision-making process. Quality assurance pertains to the systematic processes to ensure that products meet defined quality standards. The presence of this aspect in numerous studies reflects the industry's commitment to maintaining high-quality outputs, which is essential for competitiveness and customer satisfaction. Product development, mentioned twice, focused on selecting processes and materials based on the specific product under development. This aspect emphasises the importance of aligning production methods with product characteristics, capabilities, and material availability. The limited frequency of this category compared to others may suggest that while product development is crucial, it may often be integrated into broader considerations of sustainability and technical factors within decision-making frameworks [94]. Lastly, the minimal focus on the supply chain, identified only once, indicates a potential area for further exploration in future studies. Given that supply chain dynamics play a critical role in manufacturing operations, more comprehensive analyses could yield valuable insights into how decision-making tools can be applied effectively across the entire supply chain [95].

Overall, the results reflect an industry-wide trend toward integrating sustainability and technical considerations into decision-making processes, with a clear recognition of their impact on overall performance and competitiveness, which aligns with conclusions from previous studies [96,97].

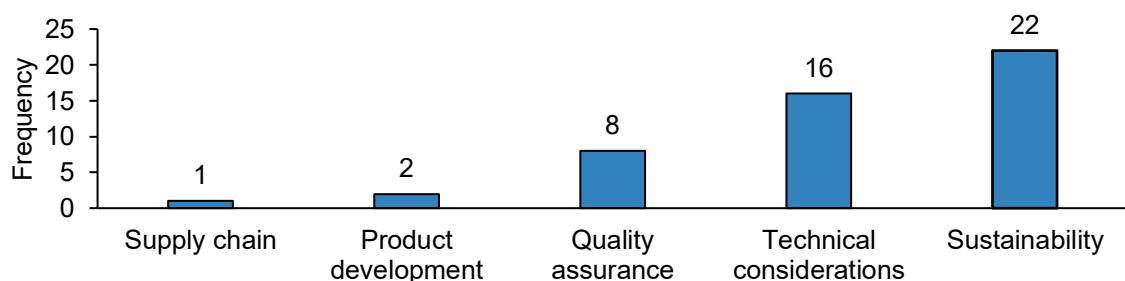


**Figure 10 Impact areas covered in the literature**

### 2.5.2 Thematic Evolution

The evolution of decision-making tools in manufacturing can be traced by examining the chronological progression of research across sectors, methods, and impact areas. This subsection explores the development trends of these tools, revealing key milestones and shifts in focus within the literature. The use of diverse methodologies has expanded in parallel with emerging industry needs, technological advancements, and an increasing emphasis on sustainability and efficiency. The heatmap in Figure 11 provides a detailed view of the evolution by mapping the publication year against the industry sectors, methods employed, and impact areas considered in each study. This visual representation reveals several important trends over time.

Regarding the sectoral focus of the studies, there has been a consistent increase in academic interest in AM, largely due to its superior flexibility and customisation potential, which allows for complex geometries and reduced material waste [98]. Another area of growing interest is machining processes, while papers focusing on more generic manufacturing methods remain the third most prevalent. It is worth noting that, contrary to prevailing expectations, sectors such as biomaterials and biofuels have not been as prominently featured. This could be attributed to the need for further technological development and refinement of these products before decision-making tools can be effectively applied to their utilisation [99]. Other sectors and groups are more scattered across the timeline, suggesting a more sporadic academic interest or niche focus in certain areas.

Regarding the methods and approaches utilised, MCDA has seen a notable increase in application, particularly in 2023. This is likely due to its ability to handle the various and often conflicting factors involved in manufacturing decision-making, such as cost, efficiency, and sustainability. Direct comparison has also been consistently used over the years, possibly because of its simplicity and the straightforward ability to contrast available options. While recognised for their analytical power, tools like deep learning and computational simulation have only started gaining traction more recently, particularly for process-level decisions.

This shift likely reflects advancements in computational technology, making these tools more accessible and applicable in real-time decision-making.

In terms of impact areas, sustainability and technical considerations have maintained a strong presence throughout the period, likely due to the increasing global emphasis on environmental concerns and the push for more efficient, technologically advanced manufacturing processes. Quality assurance, however, has only gained significant traction in the past four years, highlighting the growing recognition of the need for consistent product quality as markets become more competitive and customer expectations rise. This trend underscores a shift in focus from just optimising production to ensuring that the end products meet increasingly stringent standards.

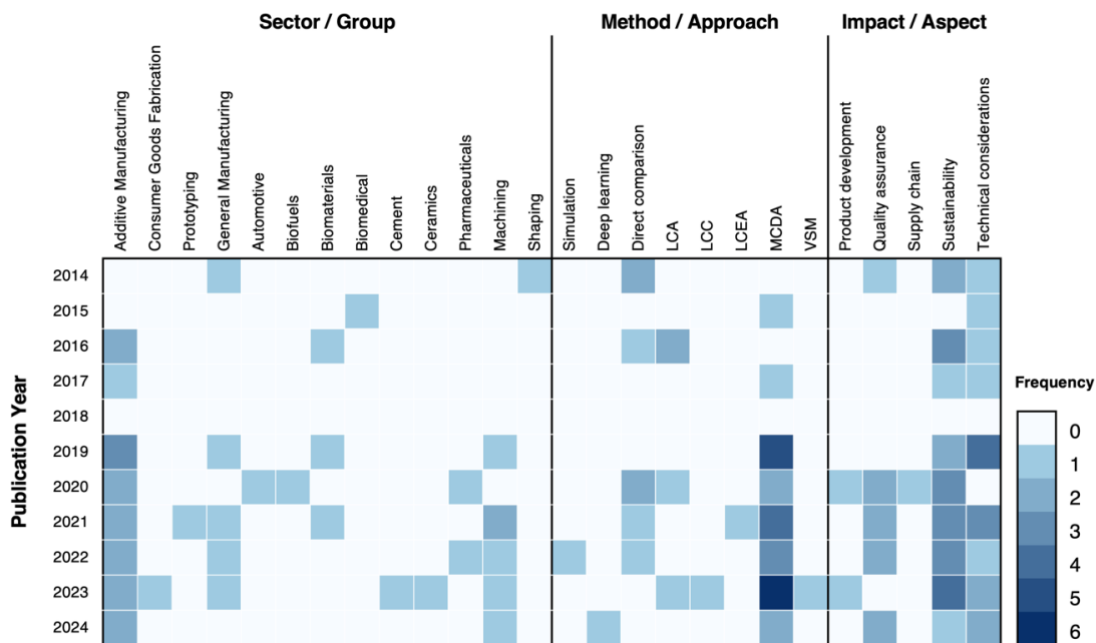


Figure 11 Thematic evolution heatmap

### 2.5.3 Cross-Thematic Analysis

The intersections of the various key parameters of the examined studies have been explored. This analysis provides key insights into how specific decision-making approaches contribute to evaluating manufacturing processes and how those evaluations ultimately influence the criteria for comparison.

### **2.5.3.1 Interactions Between Impact Areas**

The matrix presented in Figure 12 provides a detailed view of the interactions between various impact areas in decision-making tools for manufacturing. It reveals how different aspects are connected and how they have been considered in the analysed studies.

One notable finding is the prominence of quality assurance and environmental impact as key focal points across multiple intersections. Quality assurance shows significant interactions with other impact areas, including economic impact and technical considerations. This suggests that ensuring product quality is not an isolated concern but is deeply interwoven with cost efficiency and the technical feasibility of processes. Similarly, the frequent intersections between environmental impact and areas like economic impact and quality assurance emphasise the growing importance of sustainability, with many studies focusing on minimising environmental footprints while maintaining product standards and managing costs.

The central role of economic impact in the matrix further highlights the critical balance between financial considerations and other decision-making factors. The economic impact frequently appears across the matrix, particularly with environmental impact and technical considerations. This indicates that cost analysis is pivotal when evaluating environmental and technical outcomes, showcasing the increasing need for integrated approaches that combine financial viability with sustainability goals.

In contrast, supply chain considerations show relatively limited intersections with other impact areas. While they are linked to quality assurance, economic impact, and environmental impact, these connections are less frequent. This could indicate that supply chain management, though important, is often treated separately from immediate process-level decisions. However, with the growing complexity of global supply networks, future studies may need to focus more on integrating supply chain impacts into the broader decision-making framework.

Technical considerations demonstrate strong connections with multiple areas, particularly economic impact and quality assurance, further underscoring the importance of technical feasibility in the decision-making process. The significant frequency of interactions involving technical considerations suggests that many studies prioritise technological factors as essential criteria, especially when evaluating manufacturing processes' potential economic and quality outcomes.

Moreover, the Triple Bottom Line, a context for balancing environmental, social, and economic factors [100], is primarily connected to environmental and economic impact. This reinforces the idea that sustainability, while multidimensional, is often approached through the lens of environmental and economic outcomes, particularly in manufacturing sectors that aim to reduce emissions, energy consumption, and waste. The social aspect is not considered solely, but only as part of a holistic insight.

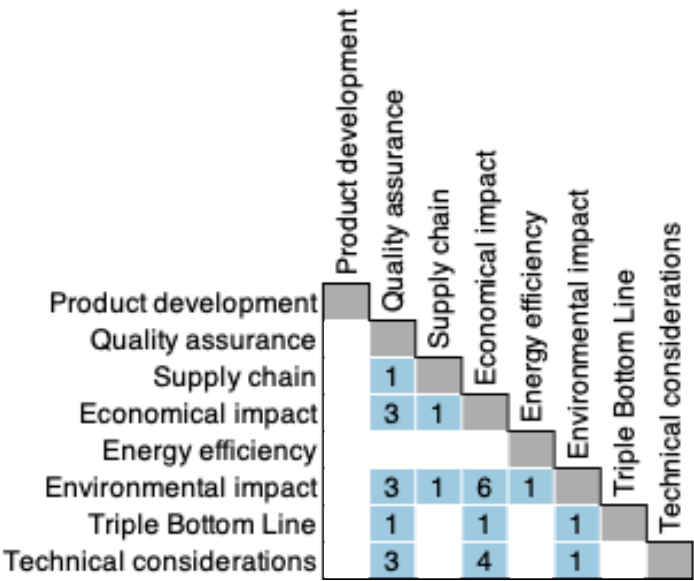


**Figure 12 The interactions of impact areas with one another**

This cross-analysis of impact areas reveals a complex interplay between economic, environmental, and technical considerations in decision-making processes. While traditional factors like cost and quality remain central, there is a clear trend towards integrating sustainability, mainly through the lens of environmental impact and energy efficiency. However, the relatively lower focus on supply chain interactions suggests that further integration of logistics and

distribution processes into decision-making tools could enhance their comprehensiveness in future studies.

### 2.5.3.2 Method, Impact area and the bases of comparison

The approaches used have been analysed regarding the impact areas they cover. Furthermore, the impact areas have been examined concerning the basis of comparison used in the assessments. This is portrayed in a Sankey diagram in Figure 13.

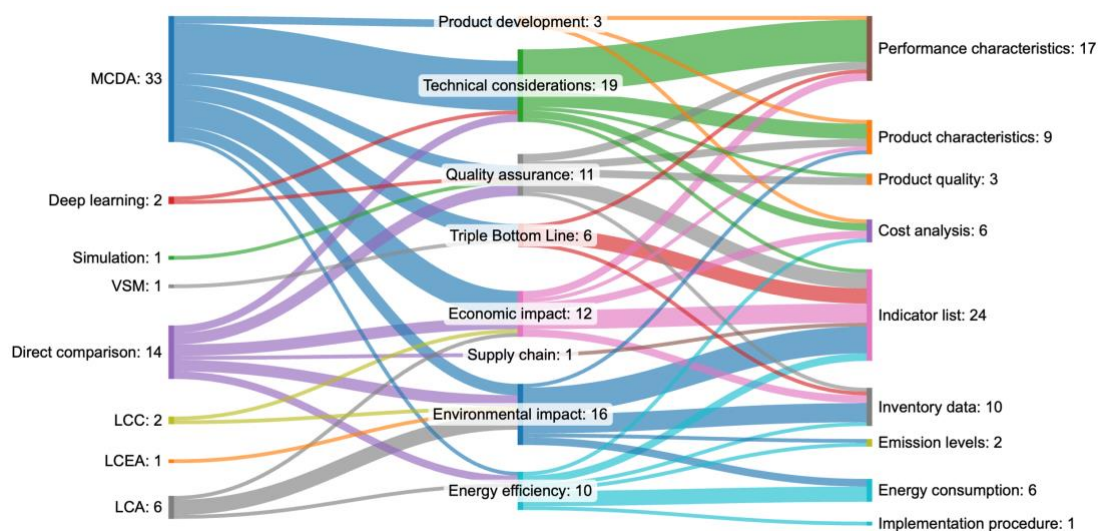


**Figure 13 Sankey methods to impact area to bases of comparison**

### Correlation of Methods and Impact Areas

The analysis of methods and their corresponding impact areas reveals key patterns in the application of decision-making tools across different objectives. Among the reviewed studies, MCDA stands out as the most versatile method, applied across a wide range of impact areas. It is particularly prominent in technical considerations. This indicates its adaptability in scenarios where trade-offs between multiple, often conflicting criteria are necessary. MCDA's application in sustainability-related areas further underscores its strength in integrating economic, environmental and technical factors, which is critical when integrating sustainability aspects in modern manufacturing contexts. Previous studies have indicated that MCDA is well-suited for environments characterised by uncertainty

and the need for stakeholder involvement, reinforcing its relevance in contemporary manufacturing contexts [101,102].

LCA is primarily associated with environmental and energy efficiency considerations, reflecting its traditional role in assessing the environmental footprint of processes and materials. Its strong focus on these impact areas aligns with the increasing demand for sustainability assessments in production systems. Similarly, LCC is used for evaluating economic impacts, indicating its utility in cost-based sustainability assessments, where economic efficiency is weighed against environmental benefits over the life cycle of products and processes. While LCA has often been applied independently, LCC was used in conjunction with LCA, allowing the two methods to complement and address each other's limitations[103]. LCEA, a more specialised life cycle technique focusing specifically on energy, has also emerged as an option for evaluating the energy consumption and efficiency of manufacturing processes. This approach allows for a deeper analysis of energy-related impacts, complementing broader sustainability assessments conducted through LCA.

Direct comparisons also show a focused but distinct pattern in their application. For instance, it appears relatively balanced across economic, environmental, technical and quality assurance impacts. This indicates its utility in straightforward benchmarking tasks where trade-offs between different criteria must be quickly compared. Interestingly, more advanced methodologies, such as deep learning and computational simulations, are beginning to emerge, linking directly to quality assurance and technical considerations. This suggests a shift towards adopting innovative computational techniques that enhance precision and optimise manufacturing processes. Incorporating these advanced methods indicates an industry trend toward leveraging technology to improve decision-making capabilities and operational outcomes.

One notable pattern is the relatively low occurrence of VSM, with its singular connection to the Triple Bottom Line, addressing environmental, economic, and social aspects of sustainability. In the instance where VSM was applied, it was used to identify root causes of inefficiencies in a manufacturing organisation and

paired with MCDA to guide improvement strategies. This suggests that while VSM is highly effective in diagnosing inefficiencies within broader systems, it is less commonly employed for individual process evaluations than more adaptable methods like MCDA or LCA, which are more frequently used across specific impact areas and goals.

### **Correlation of Impact Areas and Bases of Comparison**

From the identified impact areas, several bases of comparison emerge. Technical considerations, environmental impact, and quality assurance are frequently evaluated based on performance characteristics, product quality, and various indicators that reflect specific and measurable criteria for assessing the effectiveness of manufacturing processes. Technical aspects are mainly linked to performance characteristics, underscoring the industry's ongoing priority of optimising operational efficiency and process accuracy. On the other hand, environmental impacts are assessed more broadly through energy consumption, emission levels and inventory data, further emphasising the growing importance of sustainability in decision-making.

Economic impacts are typically assessed through cost analysis and indicator lists, reflecting the financial considerations integral to manufacturing decisions. Similarly, energy efficiency, though less frequently addressed, links directly to energy consumption and emission levels, aligning with the sector's increasing emphasis on reducing energy use and emissions. Though less prominent, supply chain considerations focus on the use of indicator lists, suggesting that supply chain metrics are still an emerging focus in integrating decision-making tools.

Additionally, the diversity in bases of comparison indicates that decision-making tools are not only about optimising one aspect but also managing complex trade-offs between various objectives, such as cost versus sustainability or quality versus efficiency. The link between emerging technologies like deep learning and traditional aspects like quality assurance suggests a gradual shift towards smarter, data-driven approaches to manufacturing decisions. The industry's growing reliance on integrated, multi-faceted methodologies like MCDA and the application of advanced technologies points towards the future of decision-

making tools, where processes are evaluated holistically, with equal consideration for economic, environmental, and technical factors. This approach enables businesses to make more informed and balanced decisions, leading to more sustainable and efficient manufacturing practices. For companies looking to adopt these tools, it is essential to understand the immediate process and how different methods, impact areas, and comparison metrics interact to inform the best course of action.

Consequently, a prominent pattern is the central role of the indicator list, which shows significant interactions across multiple areas. With the highest frequency of occurrences, utilising an indicator list with a wide span of evaluation points underscores the importance of a comprehensive outlook, enabling the evaluation of various performance aspects. This suggests that a well-defined set of indicators can be foundational in assessing manufacturing processes, ensuring that critical factors are systematically and holistically evaluated [104–106].

The interactions involving performance characteristics or capabilities, as well as product characteristics, also stand out. The high frequency of connections to performance metrics indicates that manufacturers prioritise assessing their production capabilities to ensure alignment with market demands and technical specifications. This focus on performance highlights the critical need for manufacturers to continuously evaluate their operational capacities and adapt to evolving industry standards [107]. Interestingly, the data reveals a lesser emphasis on implementation procedures. This indicates a potential gap in practical applications, where the theoretical understanding of processes does not always translate into effective execution.

The integration of methods, impact areas and bases of comparison highlights the nuanced and multi-dimensional nature of decision-making in manufacturing. MCDA emerges as the most versatile method, capable of addressing various technical, economic and environmental factors. The emphasis on these impacts underscores the industry's dual focus on optimising operational performance while adhering to sustainability goals.

### **2.5.3.3 Methods Across Operational Levels**

The analysis of decision-making techniques across different operational levels (facility, process, product and system) reveals distinct patterns in their usage, as presented in Figure 14.

Specific approaches, like Direct Comparison, demonstrate flexibility by being applied at the process level and scaling up to facility or system levels when needed. For example, performance analysis at the process level can inform broader decisions, such as facility-wide operational strategies or overall system efficiency. Additionally, some methods can simultaneously address multiple operational levels within the same study. For instance, a method applied to the process level may also aggregate data to enable comparisons or decisions at higher levels, such as system-wide evaluations [108].

Similarly, MCDA is adaptable across different operational levels, making it useful for detailed process and higher-level system assessments. However, this scaling can be complex, requiring additional layers of data, broader stakeholder engagement, and more comprehensive system-wide modelling, and therefore, it is more limited. However, methods such as LCA, LCC, and LCEA, which focus on environmental and cost assessments, are generally limited to the process and product levels. These tools are practical within their specific scope but are more challenging to apply at the facility or system levels due to their specialised focus on isolated processes or products. VSM demonstrates that it was applicable for operational improvements at the facility and system levels, indicating that its focus on optimisation at the process level can be translated upwards. This is due to the intrinsic nature of the approach [109].

Conversely, tools like computational simulations and deep learning are evolving methods used primarily for product and process analysis. Expanding their application to larger, more complex systems or facilities presents challenges due to the computational power and extensive modelling required for broader-scale use. While these tools offer significant potential for process optimisation, scaling them for facility-wide or system-level analyses while maintaining granularity is often complicated and resource-intensive.

In summary, while some tools can scale from process to facility or system levels, the complexity of this transition varies. Tools like MCDA and Direct Comparison offer more flexibility, while others like LCA and LCC remain constrained to process-level analysis. Applying tools across multiple operational levels is critical for achieving comprehensive decision-making in complex manufacturing environments, but this remains a challenge for many methodologies.

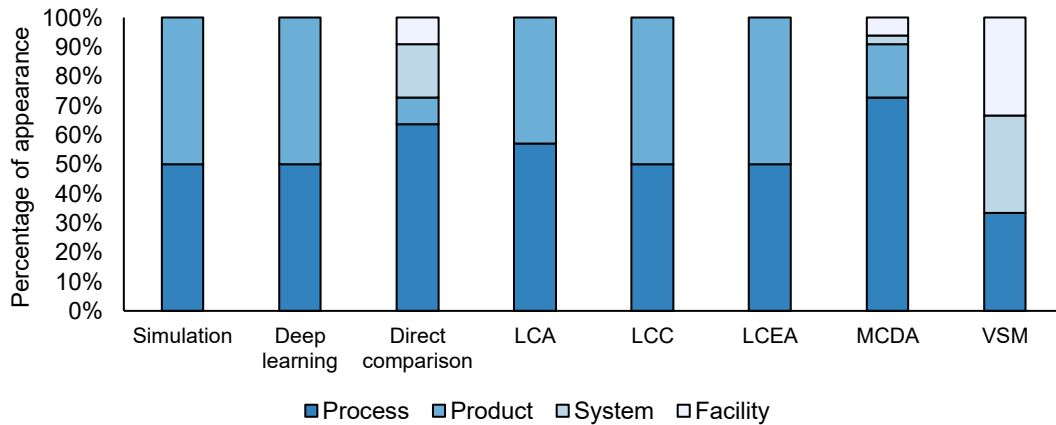


**Figure 14 Distribution of appearances of different decision-making approaches across operational levels in manufacturing systems, as reported in the literature. The percentages represent the distribution of instances where each approach is applied at the process, product, system, and facility levels. These appearances may occur across multiple levels within the same study or in different studies**

#### 2.5.3.4 Analysis of Advantages and Limitations of Identified Methods

The analysis of the advantages and limitations of the various methods and approaches used in decision-making for manufacturing, as visualised in the matrix in Figure 15, highlights some significant trends.

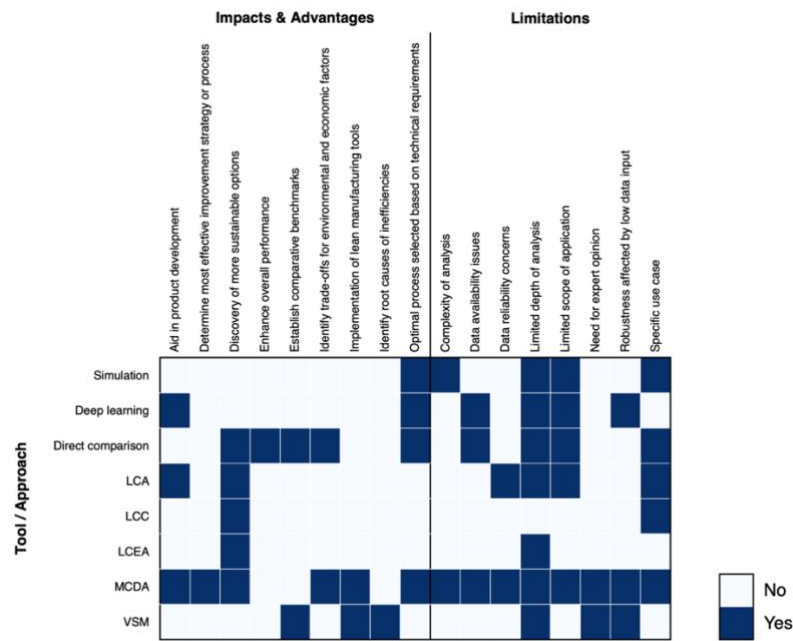


**Figure 15 Advantages and limitations of the identified approaches**

**Advantages:** MCDA emerges as the most widely applicable tool, exhibiting strengths across several areas such as product development, process improvement and identifying sustainable options. This aligns with existing literature highlighting MCDA's ability to synthesise multiple criteria in complex decision-making environments, making it particularly valuable in manufacturing contexts where trade-offs between technical and sustainability criteria are crucial [110]. Similarly, LCA was shown to aid significantly in identifying environmental impacts and establishing environmental benchmarks. This aligns with its well-established role in sustainability assessments, particularly its capacity to quantify environmental burdens across a product's lifecycle [111]. Although more limited, the presence of LCC and LCEA reflects their increasing relevance in economic and energy efficiency assessments, respectively. LCC is particularly important for cost-based sustainability assessments, where long-term financial considerations are weighed against environmental outcomes, often in conjunction with LCA to overcome mutual limitations. LCEA, though less frequently utilised, offers a more pinpointed focus on energy consumption and efficiency, which is becoming critical in the age of energy-conscious manufacturing [112].

Direct Comparison appears as an advantageous method when benchmarking between alternative strategies or processes is required. Its primary utility lies in enhancing overall performance by establishing clear comparisons between alternatives. It is critical for manufacturers seeking to optimise processes or choose between different materials, technologies, or production strategies. While direct Comparison lacks the depth to comprehensively address trade-offs across multiple sustainability dimensions, it provides significant value when a single metric or aspect is a central focus. Its effectiveness in comparative evaluation allows manufacturers to make more informed decisions based on competitive benchmarks and performance data without requiring complex modelling or extensive data inputs. This method could be further improved by incorporating weighted criteria, allowing for a more nuanced evaluation that considers the relative importance of different performance factors. By doing so, direct comparison could extend its utility beyond single-metric assessments, enabling manufacturers to balance competing objectives such as cost and environmental impact. This would allow for a more flexible and robust decision-making process, particularly in industries with crucial trade-offs between these factors.

A notable advantage of VSM is its unique capability for root cause analysis and identifying areas for improvement in manufacturing systems, demonstrated in its combined use with MCDA. While limited in standalone applications, its utility in diagnosing inefficiencies is well-recognised, particularly in lean manufacturing environments [113]. Although not as widely used as other tools, Deep Learning and Simulations offer strong potential for performance improvements by enhancing the predictive accuracy of models, which is crucial for quality assurance and technical considerations. These emerging tools, especially Deep Learning, reflect ongoing shifts toward data-driven decision-making, gaining traction as manufacturing processes become more digitised under Industry 4.0 and the recently coined Industry 5.0 [114,115].

**Limitations:** Despite these advantages, the heatmap also reveals critical limitations for each tool, some of which align with documented challenges in the literature. MCDA, while offering robust decision support, is constrained by several

key limitations. These include the complexity of analysis, data reliability issues, and weighting inconsistencies. Additionally, the absence of a discussion or review process to interpret the results can lead to oversimplified recommendations. The assumed preferential independence between criteria can further distort results, especially when interactions between criteria are not considered. Moreover, incorporating costs as a criterion often fails to capture opportunity costs adequately, leading to suboptimal resource allocation [116,117]. These challenges highlight the need for more nuanced approaches to applying MCDA effectively in manufacturing decisions.

LCA and LCC face similar challenges. Both tools, while comprehensive, suffer from high data demands and complexity in analysis, mainly when applied to diverse manufacturing processes. Studies have pointed out that the reliability of LCA results can be heavily influenced by the scope of the analysis and the assumptions made during data collection, which can limit its broader applicability in real-world manufacturing contexts [118]. LCEA, while less complex than LCA, shares data availability concerns, especially as it focuses exclusively on energy metrics without considering broader environmental or social factors.

In contrast, VSM and Deep Learning exhibit narrower application scopes. VSM's use primarily concerns identifying waste and inefficiencies within existing systems rather than offering comprehensive decision support across broader impact areas. This aligns with its traditional role in lean manufacturing, which focuses on process streamlining rather than evaluating sustainability or economic trade-offs. Deep Learning, while showing promise, is constrained by the robustness of its results, mainly when low-quality or limited data is available. Moreover, once a model has been established for a specific task, it will require many data points and further training to enable its adaptation to other projects, limiting its expansion. These challenges are well-documented in the literature on AI-driven decision tools [119–121].

Direct Comparison, while effective in benchmarking and enhancing overall performance, demonstrates limitations due to its finite use cases. It is often restricted to comparative evaluations and lacks the flexibility to offer deeper

insights into long-term strategic improvements or sustainability metrics. This limitation means direct comparison is typically used for isolated decision points or for improving specific, measurable areas rather than facilitating broader assessments of multi-dimensional challenges.

#### **2.5.3.5 Discussion and Implications**

The findings suggest a clear pattern: methods with broader applicability, such as MCDA and LCA, offer more comprehensive decision-making support, particularly in balancing sustainability and technical performance. However, they also face significant limitations related to data complexity and the depth of analysis required. This supports the argument that while these tools provide valuable insights, their practical implementation in manufacturing contexts requires careful consideration of data availability, skill requirements and the specific goals of the analysis.

Conversely, while highly effective in specific contexts, tools with narrower scopes, such as VSM, Direct Comparison, and Deep Learning, are not yet as widely applicable across multiple dimensions of manufacturing decision-making. This reflects a broader trend in the field where newer, more specialised tools, though promising, still require further refinement to broaden their use cases. Future research should explore integrating these emerging tools into more comprehensive decision-making frameworks to capitalise on their strengths without sacrificing the breadth of analysis. Additionally, the combined use of tools like VSM with MCDA suggests a trend toward hybrid approaches that could mitigate some of the limitations observed with individual tools. This opens up a potential area for future studies to investigate the efficacy of tool combinations in addressing multi-criteria decision-making challenges, especially in sustainability assessments and process improvements.

#### **2.5.4 Synthesis of Findings**

**In this section, the findings from the analysis of various decision-making tools and their respective impacts on manufacturing processes are synthesised. The tools and approaches examined vary in terms of their Impact Range, Complexity, Ease**

of Use, and Industry Applicability, each addressing different aspects of decision-making in manufacturing. The tables provided (Table 3 and

Table 4) summarise these characteristics and compare each tool's advantages and limitations.

**Table 3 Attributes used to analyse the tools and approaches**

| Attribute             | Description                                                                                                                 |
|-----------------------|-----------------------------------------------------------------------------------------------------------------------------|
| Operational scope     | How easily the tool can be scaled or applied across different operational levels (from process to facility level).          |
| Technical complexity  | The level of technical or analytical difficulty required to implement and use the tool.                                     |
| Integration potential | The ability of the tool to be integrated into existing systems or processes, particularly in a digital or automated manner. |
| User-friendliness     | The simplicity and usability of the tool for practitioners, with minimal training or setup required.                        |
| Data requirements     | The amount and complexity of data needed to use the tool effectively.                                                       |
| Trade-off analysis    | The tool's ability to scale to larger systems or processes without significant performance losses.                          |

Simulation and deep learning are powerful tools with high data requirements and technical complexity, excelling in detailed process modelling and advanced analytics. However, they are less user-friendly, requiring specialised expertise and substantial infrastructure, limiting their wider application across industries. In contrast, Direct Comparison is a more straightforward, more accessible tool with low complexity and minimal data needs, making it ideal for quick benchmarking. Its high user-friendliness allows rapid deployment, but it is less effective for complex, multi-tiered analysis across different variables. LCA and LCC offer in-depth sustainability and cost analyses, though both require significant data and are limited in operational scope. While these tools provide robust trade-off analyses, their complexity restricts broader usability without sufficient expertise and resources. MCDA provides a structured approach to decision-making that is well-suited for complex, multi-criteria scenarios, but it requires a time-intensive setup and is not easily executable. Meanwhile, VSM is cost-effective and user-friendly, best suited for identifying value-adding steps and eliminating waste. However, its effectiveness might be limited across impact areas without customisation or integration with additional tools.

**Table 4 Summary rating of each tool or approach based on various attributes**

| Approach          | Operational Scope | Technical Complexity | Integration Potential | User-Friendliness | Data Requirement | Trade-off Analysis |
|-------------------|-------------------|----------------------|-----------------------|-------------------|------------------|--------------------|
| Simulation        | ★★★★☆             | ★★★★☆                | ★★★★☆                 | ★★☆☆☆             | ★★★★★            | ★★★★☆              |
| Deep learning     | ★★☆☆☆             | ★★★★★                | ★★★★☆                 | ★★☆☆☆             | ★★★★★            | ★★★★☆              |
| Direct comparison | ★★★★☆             | ★★☆☆☆                | ★★☆☆☆                 | ★★★★★             | ★★☆☆☆            | ★★★★☆              |
| LCA               | ★★☆☆☆             | ★★★★☆                | ★★★★☆                 | ★★★★☆             | ★★★★★            | ★★★★☆              |
| LCC               | ★★☆☆☆             | ★★★★☆                | ★★★★☆                 | ★★★★☆             | ★★★★☆            | ★★★★☆              |
| LCEA              | ★★☆☆☆             | ★★★★☆                | ★★☆☆☆                 | ★★★★☆             | ★★☆☆☆            | ★★★★☆              |
| MCDA              | ★★★★☆             | ★★★★★                | ★★★★☆                 | ★★☆☆☆             | ★★☆☆☆            | ★★★★★              |
| VSM               | ★★★★☆             | ★★★★☆                | ★★☆☆☆                 | ★★★★☆             | ★★☆☆☆            | ★★☆☆☆              |

The synthesis of findings underscores the importance of selecting decision-making tools based on the specific needs of the manufacturing process and the desired impact areas. Tools like Simulation, deep learning, and MCDA are ideal for comprehensive, data-heavy evaluations but require significant expertise and infrastructure. More straightforward tools like Direct Comparison and VSM offer easy-to-use functionality for targeted applications but lack the versatility of more complex tools. As manufacturing processes evolve, particularly under the influence of Industry 4.0 and sustainability imperatives, a hybrid approach that leverages multiple tools in tandem may offer the best pathway to balancing trade-offs and achieving long-term sustainability goals.

## **2.6 A Practical Guide for Effectively Integrating Decision-Making Tools in Manufacturing Settings**

Despite the significant strides made in developing decision-making tools for manufacturing processes, crucial gaps still limit their full utilisation. Among these is the lack of adoption of emerging Industry 4.0 technologies like IoT, AI, and real-time data processing. Furthermore, insufficient attention has been given to integrating these tools into fully functioning manufacturing environments. Many studies overlook key steps required to smoothly incorporate decision-making tools within operational systems, from data acquisition and sharing to real-time

processing and long-term monitoring. Furthermore, strategic alignment, system-wide incorporation and skill requirements are rarely discussed. This gap is evident in the fact that none of the covered literature provided clear guidance on how these tools can be seamlessly integrated into a real-world manufacturing context.

In response to these gaps, a structured guide has been developed to facilitate the smooth integration of decision-making tools into manufacturing systems, presented in Figure 16. This step-by-step process emphasises four critical areas: Data & Integration, Management & Operations, AI, and Research & Development. Each area is subdivided into key actionable steps spanning three phases: pre-implementation, during implementation, and post-implementation. By aligning these phases with specific tasks in data handling, technology integration, and team training, businesses can ensure a seamless transition from planning to execution. The guide provides a comprehensive guide to harnessing the full potential of decision-making tools, supported by real-world justifications and insights from recent research.

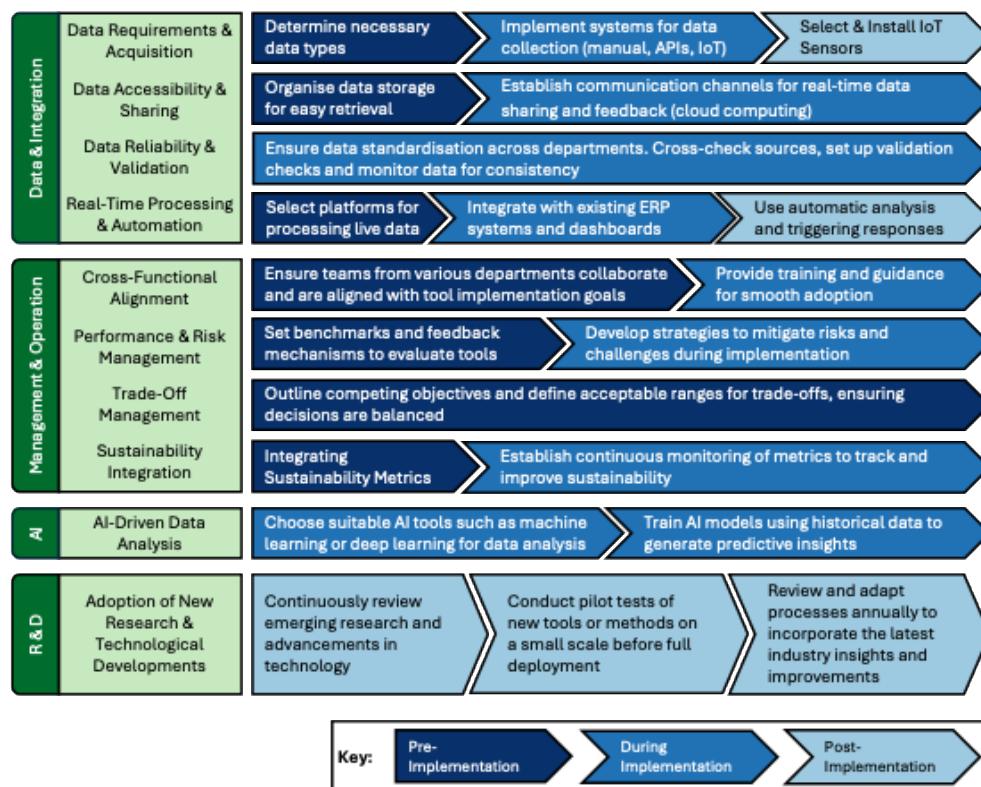


**Figure 16 Structured guidelines for decision-making tool integration in manufacturing systems, highlighting phased implementation**

### **2.6.1 Data Management and Tool Integration**

Effective data management is essential for the successful use of decision-making tools. In the pre-implementation phase, the priority is identifying the necessary data types and ensuring data storage systems are organised for easy retrieval. During implementation, businesses should focus on establishing data acquisition and real-time data-sharing mechanisms, such as cloud platforms, to facilitate continuous communication between departments [122]. Data validation and standardisation must also be prioritised to ensure consistency across the organisation [123]. In the post-implementation phase, installing IoT sensors tailored to ongoing data collection needs will allow continuous monitoring and refinement of decision-making processes [124]. This allows businesses to harness data as a central asset, driving more informed and timely decisions.

### **2.6.2 Managerial and Operational Preparation**

Cross-functional alignment is critical to the successful adoption of decision-making tools. In the pre-implementation phase, all departments must be aligned with the implementation goals to avoid fragmentation or miscommunication [125]. Ensuring that operations, IT, and management team members work cohesively is essential. Moreover, benchmarks should be set to evaluate the tools' impact and prepare feedback mechanisms for ongoing assessments. As implementation progresses, comprehensive training should be provided to ensure all employees are proficient with the new tools. Training should focus not only on using the tools but also on understanding their implications for decision-making. Risk mitigation strategies should also be developed to address potential challenges, ensuring the smooth integration of tools without disrupting ongoing processes [126]. Managing trade-offs is another key area of focus. Businesses should identify competing objectives and define acceptable ranges for trade-offs [127]. For example, companies may need to decide how much cost can be sacrificed for environmental gains. During implementation, this balance must be maintained by closely monitoring the trade-offs in real-time.

### **2.6.3 AI Integration**

AI is central to modern decision-making, offering advanced capabilities for analysing data, predicting outcomes and optimising manufacturing processes [128]. Businesses should identify specific decision-making challenges AI can address, such as predictive maintenance, energy optimisation or production scheduling [129–131]. Selecting suitable AI models (e.g., machine learning, deep learning) based on data availability and complexity is critical. Preparing high-quality, standardised datasets is essential for effective model training. Subsequently, AI models should be trained using historical and real-time data to generate actionable insights. Integration with existing systems, such as Enterprise Resource Planning (ERP) platforms, ensures seamless feedback for decision-making. Regular validation and fine-tuning of AI models maintain their relevance as operational conditions evolve [132]. Ongoing monitoring and refinement of AI systems are essential to ensure continuous improvement. Real-time data from IoT sensors can enhance the adaptability of AI tools [133]. Periodic updates and evaluations allow AI systems to incorporate advancements and align with changing operational goals. AI can significantly improve decision-making accuracy by analysing large datasets far beyond human capacity, providing actionable insights that drive operational improvements, and reducing costs and downtime while improving efficiency [134,135].

### **2.6.4 Research & Development (R&D)**

Continuous improvement is key to long-term success. Post-implementation, businesses must stay updated on the latest technological advancements by reviewing industry trends and conducting small-scale pilot tests before full deployment. This approach enables organisations to refine their tools and processes, ensuring that they remain competitive and adaptable to evolving industry standards. Regular reviews will allow businesses to incorporate cutting-edge developments and maintain optimal performance.

### **2.6.5 Leadership Support and Technology Scalability**

Ongoing management and leadership involvement are essential for ensuring that the integration of decision-making tools aligns with overarching business goals. Support from leadership teams can drive successful adoption by providing the necessary resources, setting priorities, and ensuring cross-departmental alignment. Without leadership backing, the implementation process may lack direction or stall altogether [136].

One of the key challenges businesses face is the evolving nature of technology. Companies must remain adaptable by integrating new decision-making tools and upgrading the infrastructure around them. Scalability should be a priority from the outset, allowing businesses to adjust their decision-making tools to accommodate future growth or changes in operational demands. As the tools evolve, businesses should stay open to upgrading their technology, ensuring that they continue to provide value over time.

### **2.6.6 Summary**

The successful integration of decision-making tools into manufacturing is not just a technical challenge but also an opportunity for collaboration between industry and academia. Future research should focus on creating more adaptable, robust, and industry-specific tools that can address both current and emerging challenges. By fostering stronger partnerships between academic researchers and manufacturing professionals, we can ensure that the next generation of decision-making tools will be even more effective, scalable, and sustainable. This guide provides an actionable framework for integrating decision-making tools into manufacturing operations, ensuring that businesses can harness the full potential of these tools.

### **2.6.7 Practical implications**

The framework provides a structured approach to integrating decision-making tools into manufacturing, addressing challenges in data handling, scalability, and workforce readiness. By aligning with Industry 4.0 and sustainability goals, it ensures tools are adaptable to evolving needs while improving operational

efficiency. Businesses can use this phased approach to implement tools effectively, from pre-implementation planning to post-implementation monitoring, enabling continuous improvement and long-term competitiveness.

## **2.7 Conclusion**

This study presents a comprehensive analysis of decision-making tools in manufacturing systems, offering both a thematic overview and an in-depth discussion of their practical applications across various operational levels. Through the review of selected research papers, several key insights emerged that hold important implications for both practice and future research.

The thematic analysis identified MCDA as the most commonly utilised tool, especially due to its ability to evaluate multiple conflicting criteria in complex decision-making environments. The increased adoption of sustainability-focused methods, such as LCA, highlights the growing importance of environmental considerations in the manufacturing sector. However, the limited application of LCA across studies indicates that there is potential for greater integration of sustainability metrics into decision-making frameworks. Tools like direct comparison and VSM were also prominent, emphasising the balance between simplicity and comprehensive analysis when selecting tools that fit specific manufacturing needs.

An important takeaway is the varying degrees to which these tools can be applied across different operational levels. While methods like MCDA and direct comparison provide valuable insights at the process level, they also possess the potential to inform higher-level decisions at the facility level. This adaptability, however, depends on the complexity of the tool. Advanced methods like deep learning and computational simulations, while powerful for process-level analysis, face challenges in scalability due to data requirements and computational complexity. These findings reinforce the need for both adaptable and specialised tools to address different decision-making needs across operational scales.

This research contributes to the field of manufacturing systems by outlining the current landscape of decision-making tools, shedding light on trends such as the

growing reliance on data-driven methods and highlighting the continuous effort to integrate sustainability into manufacturing processes. Additionally, the guidelines provided outline essential steps for businesses looking to adopt decision-making tools in an increasingly digitised and data-driven environment, focusing on areas like AI integration, data management and scalability, which are critical in an increasingly digitised and interconnected manufacturing environment.

For academia, this study provides a foundation for future research into the development of more adaptable and multi-functional decision-making tools. Researchers can build on this work to explore synergies between existing tools, investigate their integration with real-time data and AI, and design frameworks that consider environmental, economic and social dimensions. Practitioners can leverage the provided guide to effectively implement decision-making tools, addressing challenges such as data standardisation, user-friendliness and scalability. By aligning operational strategies with technological advancements and sustainability goals, particularly within the context of Industry 4.0, practitioners gain actionable insights to enhance both competitiveness and regulatory compliance.

This work directly supports several SDGs by promoting sustainability and efficiency in manufacturing processes. Tools like LCA and sustainability metrics contribute to Goal 12 (Responsible Consumption and Production) by fostering resource efficiency and minimising environmental impacts. The integration of AI and data-driven methods aligns with Goal 9 (Industry, Innovation, and Infrastructure) by advancing innovation and enhancing manufacturing technologies. Furthermore, the emphasis on scalability, user-friendliness, and workforce readiness addresses Goal 8 (Decent Work and Economic Growth) by ensuring inclusive adoption of advanced tools across diverse manufacturing environments.

Common future directions include enhancing the integration of decision-making tools with real-time data and AI-driven analytics to improve responsiveness in dynamic manufacturing environments. Further research is needed to develop multi-dimensional frameworks that incorporate environmental, economic and

social metrics functioning within and across sectors. Simplifying tools to increase user-friendliness and scalability remains a priority for wider adoption, alongside improving data standardisation for greater reliability, particularly for data-intensive methods. Additionally, there is significant potential for these tools to optimise entire supply chains and manufacturing ecosystems, contributing to a sustainable and resilient industrial future.

## **2.8 Contribution of Paper to Thesis Objectives**

This paper provided a critical foundation for the thesis, fulfilling Objective 1 by delivering an in-depth, structured synthesis of decision-making tools applied at the process level in manufacturing. Through the analysis of 37 peer-reviewed studies, the review reveals how tools such as MCDA, LCA, direct comparison, and emerging AI-driven methods are applied across different sectors and operational levels. It highlights key patterns in tool usage, the industries they target, and the metrics they support, offering a thematic categorisation based on impact areas, decision levels, and tool advantages and limitations.

The study makes several contributions. First, it exposes critical gaps in current practice, such as the underuse of sustainability metrics, scalability limitations, and the lack of integration frameworks for real-world implementation. Second, it proposes a structured roadmap for improving tool deployment across industrial settings, considering aspects such as data management, AI integration, and operational readiness. This roadmap provides practical insights that guide future chapters in developing and validating tailored benchmarking frameworks and sustainability KPIs.

Finally, the paper helps position the thesis within broader manufacturing challenges, contributing to both the academic understanding of decision-making tools and their operational relevance. Its findings inform the methods and priorities addressed in the subsequent chapters, supporting the development of robust, transferable, and process-focused sustainability tools for manufacturing systems.

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## **3 Defining and Structuring Environmental KPIs for Manufacturing Operations**

### **3.1 Papers Linkage to Research Aim and Objectives**

This chapter directly addresses Objective 2 of the thesis, which seeks to define and structure environmental KPIs that enable continuous sustainability improvement in manufacturing operations. This chapter builds on two connected studies that tackle a pressing issue in industry. It focuses on the current lack of a structured and validated method for identifying and applying relevant environmental KPIs at the process level.

The first paper explores current practices across industrial sectors to understand how energy-related metrics are selected, used and interpreted. Through surveys and expert interviews, this study identifies inconsistencies in metric use and reveals challenges in metric quality, data availability, and measurement procedures. These insights inform the groundwork for KPI evaluation by highlighting the industry's perspective on metric suitability and limitations.

Building on this empirical foundation, the second paper presents a structured framework for selecting environmental KPIs tailored to manufacturing. This framework introduces a categorisation method that aligns sustainability goals with manufacturing operations, incorporates ISO-defined selection criteria, and uses a ranking methodology validated by industry and academic experts. By combining a literature-derived KPI database with practical evaluation tools, the framework ensures the selection of indicators that are both relevant and goal-oriented.

Together, these papers establish a methodical approach to KPI definition and use, addressing gaps in current sustainability assessment practices while advancing the thesis's overall aim to improve process-level decision-making in manufacturing.

## **3.2 Energy Benchmarking of Manufacturing Processes in Foundation Industries <sup>2</sup>**

### **3.2.1 Introduction**

Severe environmental pollution is the outcome of significant energy use and emissions. Manufacturing processes have come under increasing scrutiny as the industry seeks ways to reduce its environmental impacts. Energy consumption is a crucial area of focus, as the manufacturing sector accounts for 38% of global energy consumption [1]. Thereby, it is responsible for up to 25% of global CO<sub>2</sub> emissions, with much of it coming from process energy and electricity consumption [2]. To reduce these emissions, it is crucial to reduce energy consumption in manufacturing. One way to achieve this is through the use of more energy-efficient equipment and processes [3,4]. Another approach is to use renewable energy to power manufacturing processes [5]. These energy sources have a lower carbon footprint, and their energy generation process does not produce greenhouse gas emissions. However, it is not always clear which areas to tackle first, and which change will have the most effect.

Benchmarking energy consumption is a crucial step in identifying areas for improvement in manufacturing processes [6]. Through the process of comparing energy utilisation data to industry standards or to similar operations, manufacturers are able to gain a comprehensive understanding of their energy consumption and determine areas that require optimisation. The utilisation of both external and internal benchmarking methods is essential in this endeavour [7]. External benchmarking entails comparing a company's energy consumption to that of other companies within the same sector, utilising publicly available data from reputable organisations. This allows for the identification of areas for improvement through the provision of a valuable external perspective on a company's energy consumption [8]. Internal benchmarking, on the other hand, involves comparing a company's energy consumption across different operations

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<sup>2</sup> S. Sarfraz, Z. Sherif, M. Jolly, and K. Salonitis, "Energy benchmarking of manufacturing processes in foundation industries," *Procedia CIRP*, 2023.

within the same facility or between different departments. This approach enables manufacturers to identify variations in energy consumption and target areas of the facility where the greatest improvements can be made [9].

Regular monitoring and benchmarking of energy consumption can aid manufacturers in identifying areas for improvement in energy efficiency, reducing costs, and decreasing their environmental impact [10]. Furthermore, it allows manufacturers to track the success of their energy-saving initiatives over time and make necessary adjustments to continue to improve.

Benchmarking is the process of determining the highest standards of excellence for processes, goods, or services - often referred to as "best practices" - and then implementing the necessary improvements to meet those standards [11]. Although benchmarking is a useful tool, it has some limitations, such as a "best practice" cannot simply be adopted and implemented into one's organisation. Before adopting a process, one must consider how things are currently done, the culture in place, the human resources being used, etc. The majority of companies employ benchmarking as an information tool to promote continuous improvement and acquire a competitive edge. Some questions should be answered before implementing benchmarking, i.e., what will be assessed or compared and who the organisation should use as a standard or reference point for comparison [12].

In recent years, there has been an increasing number of initiatives that companies have focused on tracking the performance of their operations concerning energy consumption and utilisation. This tracking is typically achieved through the collection of Key Performance Indicators (KPIs), indicators, or metrics, referred to collectively as "metrics" in this article. Despite the wide array of metrics available for tracking energy consumption and utilisation, many organisations struggle to select a meaningful and effective set of metrics for their operations. This is in part due to the lack of consideration given to the impact that the choice of metrics can have on decision-making processes [13].

As a result, manufacturing companies have faced challenges in determining which metrics to use for evaluating their processes and how to interpret these metrics in order to drive improvements in energy efficiency and utilisation [14].

Given the complexity of the field and the profusion of metrics available, it is imperative that a systematic approach be taken to ensure that the most relevant and useful metrics are selected. This will enable organisations to make informed decisions and drive progress towards a sustainable future.

Energy metrics found in literature could be broad, such as energy efficiency [15,16], energy or fuel consumption [17], or they could be limited to sustainability, such as the ones suggested by Salwa et al. [18], including renewable energy use.

Metrics provide a systematic way of measuring and evaluating the performance of energy utilisation in the foundation industries. While there are numerous metrics available in the literature for industry use, it is important to note that their implementation and utilisation may not always be optimal. It is often that industries either do not use these metrics or do not use them to their full potential [19]. Furthermore, existing research has not thoroughly investigated the industries' actions in utilising these metrics, which can provide valuable insights into the most effective metrics and associated information gathering practices. By incorporating the views of industry and subject matter experts, this study aims to provide a comprehensive and objective evaluation of the available metrics and ultimately recommend the most effective metric for benchmarking energy utilisation. Kibira et al. [20] highlighted that having a set of selection criteria to guide the selection of metrics ensures that the chosen metrics effectively reflect the operation or parameter being evaluated. Therefore, selection criteria (defined by ISO 22400 [21]) have been used to evaluate suitable metrics for energy benchmarking while incorporating the views from industry and subject matter experts.

In the next section, the research methodology adopted in this study is presented. Section 3 describes the obtained results and discusses their implications. Finally, section 4 concludes the paper.

### **3.2.2 Methodology**

The selection of metrics for benchmarking energy use in foundation industries is crucial for identifying areas for improvement and determining the effectiveness of

the manufacturing processes. The methodology adopted in this study started with a literature review, which helped to identify and explore the metrics and benchmarking approaches presented in published research. Next, two surveys were launched, aiming to filter down the selection criteria and evaluate the metrics utilised by industry. In the final stage, interviews were conducted to ascertain the perspective of industries regarding the benchmarking metrics to be used.

#### **3.2.2.1 Criteria filtration survey (Survey 1)**

Survey 1 was designed to filter the selection criteria by assessing their importance and relevance in determining the most effective metrics to use in benchmarking energy use. The selection criteria were obtained from ISO 22400 [21] and included parameters such as accuracy, automation, cost-effectiveness, standardisation, etc. A full list is available in 8Appendix C (Table C.1). The survey consisted of a 4-point Likert scale ranging from "not important at all" to "extremely important", where participants were asked to rate the importance of each selection criterion. It was circulated among a sample of academics and industry experts, who were considered to have the relevant knowledge and expertise to provide meaningful responses. The responses were collected and analysed to determine the most important criteria that should be considered when selecting metrics for benchmarking energy use.

The survey was conducted to gather insight from experts in the field and provide a comprehensive understanding of the importance of different selection criteria in benchmarking energy consumption and utilisation. It ensured that the selection of metrics for benchmarking was based on expert opinion and relevant industry standards. By prioritising the most important selection criteria, the study aims to provide a comprehensive procedure for the selection of metrics for benchmarking energy use in foundation industries.

#### **3.2.2.2 Metrics evaluation survey (Survey 2)**

In order to gather insights from industry experts on the practical implementation of energy consumption and utilisation metrics in their organisations, Survey 2 was conducted. This survey aimed to explore the current state of energy

benchmarking practices in industry and to identify the challenges and opportunities for improvement. In particular, various energy metrics were presented in which participants selected which criteria satisfy the metrics that is/has been used to monitor processes in their organisation. If no criteria are selected, then an assumption is made that the metric has not been used by the organisation.

The methodology used for evaluating metrics is adapted from Sherif et al. [21], who created a database to collect metrics that represent manufacturing operations ranging from the organisational level down to the process level. The energy-related metrics at the process level that have been extracted are:

- Energy consumption
- Fuel consumption
- Electricity consumption
- Energy efficiency
- Energy intensity
- Waste energy
- Renewable energy
- Renewable electricity

### **3.2.2.3 Data collection Interviews**

After conducting the surveys, interviews were organised with industries to provide a more comprehensive understanding of the usage of the identified metrics within the context of the organisations. These interviews aimed to gather actual data on the metrics from the industries, in order to analyse the real-world application of the metrics. The collected data helped to shed light on how the metrics were being used by the organisations and to what extent they were effective in measuring the desired outcomes. The interviews proved to be a valuable complement to the research, providing a more in-depth understanding of the metrics and their implementation in the manufacturing industry.

### 3.2.3 Results and discussion

#### 3.2.3.1 Survey 1 results

The results of the survey were based on a statistical measure known as a 95% confidence interval, which provides a range of values that are likely to contain the true population value with 95% probability [22]. This indicates that the results of the survey are highly reliable and trustworthy. The survey aimed at determining the most suitable criteria for evaluating the performance of energy-related metrics in the manufacturing sector, where 7 out of 18 criteria were selected, as presented in Table 5.

**Table 5 Filtered criteria – results based on survey 1**

| Criteria       | Definition [21]                                                                                                                                                                                                                                                     |
|----------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Quantifiable   | The value of the metric can be numerically specified; if uncertainty is present, it should also be quantified.                                                                                                                                                      |
| Relevant       | The metric enables performance improvement in the target operation, demonstrates real-time performance, allows the accurate prediction of future events, and reveals a record of the past performance valuable for analysis and feedback control.                   |
| Understandable | The meaning of the metric is comprehended by team members, management, and customers, particularly with respect to corporate goals.                                                                                                                                 |
| Accurate       | The measured value of the metric is close to the true value, where a departure from the true value can be affected by poor data quality, poor accessibility to the measurement location, or the presence of substandard measurement devices and methods.            |
| Comparable     | Means are defined to reference supporting measurements over a period of time, and a normalizing factor to express the indicator in absolute terms with appropriate units of measure.                                                                                |
| Documented     | The instructions for implementation of a metric are up to date, correct, complete, and unambiguous, including instructions on how to compute the metric, what measurements are necessary for its computation, and what actions to take for different metric values. |
| Trackable      | The appropriate steps to take to fix a problem are known, documented, and accessible, where the particular problem is indicated by particular values or temporal trends of the metric.                                                                              |

#### 3.2.3.2 Survey 2 results

A full selection of criteria for a metric indicated a high degree of effectiveness, while the absence of a selection indicated that the metric was not in use or under consideration. As seen from Figure 17, the results showed that the metric of "energy consumption" was most widely utilised based on the total number of

responses and all criteria were selected for it, followed by other consumption metrics for electricity and fuel. However, this does not necessarily indicate them as the most effective, as all criteria were also selected for other metrics. The only metric that did not have all criteria selected was "energy waste". Notably, the criterion of "quantifiability" was the most selected for all metrics.

For further examination of the discrepancies within and across the sectors, the results of 2 foundries, 2 chemical industries and 2 glass industries were compared. Figure 18 portrays the responses in which the number of bars represents the number of metrics used by the industries, and the height of the bar signifies the quality of the metric based on the number of criteria selected for that metric. It can be seen that there is a high variance of responses within as well as across the sectors. For instance, foundry A is prevailing in tracking their energy consumption and utilisation as they employ a larger number of metrics with higher quality compared to foundry B. On the other hand, while chemicals A utilises metrics with higher quality, chemicals B tracks a larger number of metrics in which they also track their renewable energy consumption.

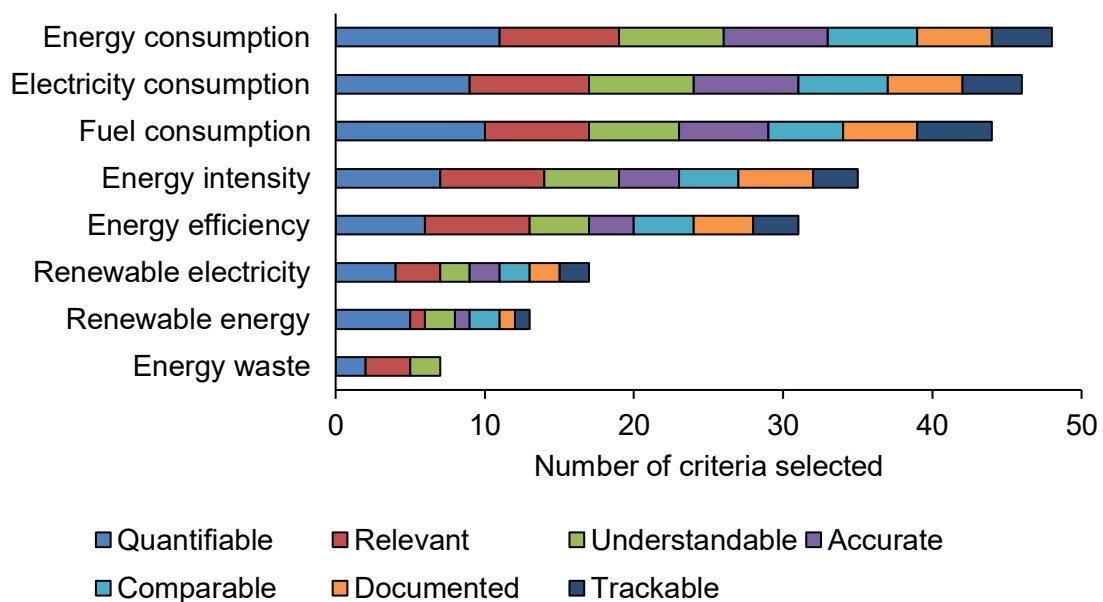


**Figure 17 Energy metrics usage and effectiveness – results based on survey 2**

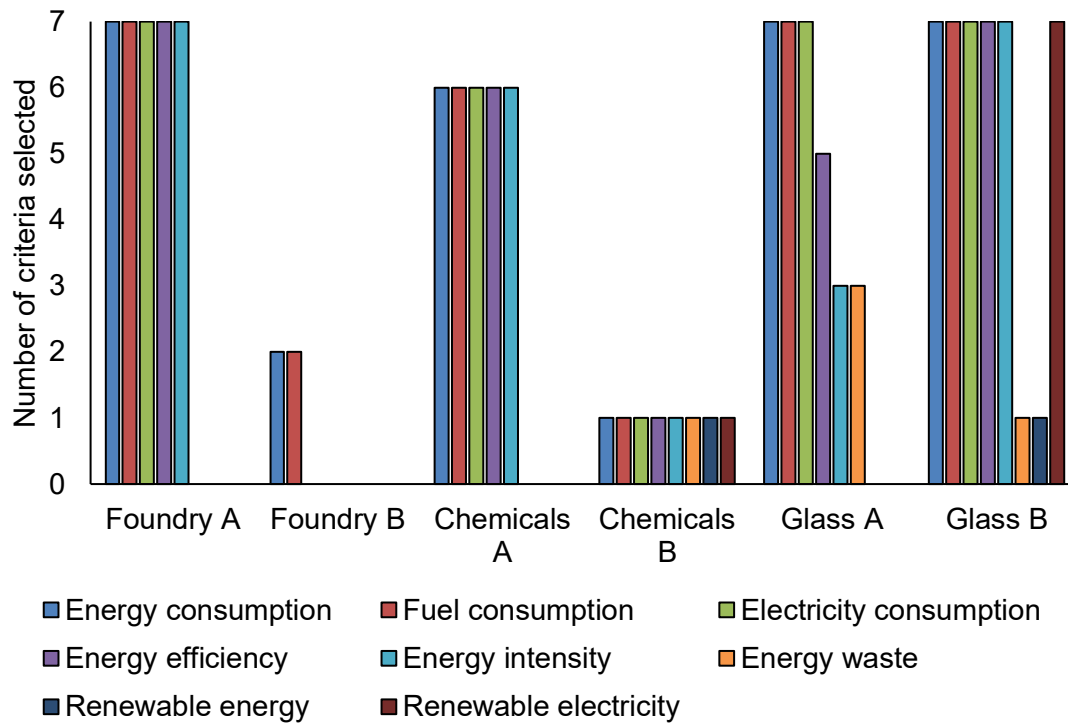


**Figure 18 Metrics evaluation by industry: quality vs. quantity**

### 3.2.3.3 Interviews results

The final phase involved conducting interviews with two metal foundries (denoted as company A and B) to investigate the energy consumption of their processes and their metrics utilisation. Company A measured its energy consumption by reading electricity meters on-site and using invoices from the energy company, which provided data on their total consumption. Then they calculated the consumption per process based on theoretical percentages, although this method of measuring the energy consumption is not entirely accurate. Nevertheless, the procedure was well-defined, and it was performed regularly, usually on a monthly basis. On the other hand, company B had its equipment embedded with a system that provided more accurate real-time energy consumption values. These results provide insight into the different methods used by foundry industries to measure and track their energy consumption and the factors they prioritise. The findings may be useful for developing benchmarking methodologies and enhancing energy efficiency in the foundry industry.

Both companies indicated that they track their energy consumption for the purpose of identifying areas of improvement to maintain their competitiveness and reduce the cost of their operations. Table 6 presents the energy consumption values for the melting process, a highly energy-intensive process, for both companies, as well as the theoretical minimum and best practice values. It can be seen that the values greatly differ between the two companies, which could be due to a variety of factors. Mainly, the method of measuring in which company A relies on estimates which could be inflating their values. Moreover, differences in scrap geometry, material composition and shift patterns could also lead to contrasting values.

The results indicate the need for an accurate and reliable method to extract values for energy benchmarking. Proper procedures must be in place to ensure the data is collected consistently and uniformly across different processes and organisations. Such procedures should be well-defined and transparent to allow for easy replication and verification. A key factor in reducing energy consumption for the melting process is improving the efficiency of the furnace, which reduces the energy consumed per unit of metal melted. The debate between cost-saving and energy-saving presents a challenge, as using a gas-fired furnace can reduce costs but results in poor melt quality and higher hydrogen content, which requires additional degassing. However, higher quality raw materials and training furnace operators are recommended to reduce metal loss through oxidation and dosing, which lowers energy consumption. Additional energy efficiency measures can include improving air compressors, reducing metal charging frequency, and using correctly sized equipment [23]. All these key factors contribute towards energy-efficient values for the melting process.

**Table 6 Energy consumption data (in kWh/t) of the interviewee companies, theoretical minimum and best values are adapted from [24]**

| Company A | Company B | Theoretical minimum | Best practice |
|-----------|-----------|---------------------|---------------|
| 1596-1824 | 500-740   | 351                 | 538           |

### **3.2.4 Conclusion**

In this study, we identify suitable metrics for energy benchmarking of manufacturing processes based on the selection criteria (defined by ISO 22400), incorporating the views from industry and subject matter experts.

The first survey was aimed at determining the most suitable criteria (7 out of 18) for evaluating the performance of the metrics in terms of energy consumption and utilisation in the manufacturing sector. The second survey identified the most used metrics (energy consumption) as well as their effectiveness based on the distinguished criteria from survey 1. The use of metrics for benchmarking is an essential part of assessing the performance of energy utilisation within the foundation industries. Metrics allow for the quantitative evaluation of various aspects of the energy consumption and utilisation process, providing a clear and objective means of comparison. By using consistent and reliable metrics, companies can identify areas of inefficiency and develop strategies for improvement, leading to reduced energy consumption and increased cost savings.

The interviews conducted with two metal foundries revealed the different methods used by the industry to measure and track their energy consumption. Company A relied on meter readings and invoices from energy companies to estimate their consumption per process, while Company B had real-time data from embedded systems. Both companies prioritise energy consumption values for the purpose of identifying areas of improvement and reducing operational costs. However, the values obtained differed greatly, highlighting the need for accurate and reliable methods of data collection for benchmarking purposes. In order to collect data consistently and uniformly across processes and organisations, appropriate procedures must be in place. These procedures should be clear and well-defined to enable easy replication and verification. The findings provide valuable insight into the industry's perspective on the importance of criteria and can inform the future plan to develop effective methods for benchmarking various aspects of the processes in the manufacturing sector.

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### **3.3 Identification of the Right Environmental KPIs for Manufacturing Operations: Towards a Continuous Sustainability Framework <sup>3</sup>**

#### **3.3.1 Introduction**

The concept of sustainability was pioneered by a report published in 1987 by the World Commission on Environment and Development (WCED). This initiated the vast research on the matter and the incorporation of this notion in all aspects of life, from individuals to corporations and whole countries all over the world [1,2]. A prominent concept followed in 1997, which considered the construction of sustainability was based on three pillars [3], known as the triple bottom line (TBL), which correlates the sustainable systems to social, economic and environmental positions [4,5].

Accordingly, many organisations are under pressure from their stakeholders to identify performance in terms of TBL as a method to present a broader perspective rather than reporting in terms of a particular aspect (i.e., cost) [6–8]. It is worth mentioning that such pressure could be imposed internally by management by setting environmentally guided targets [9] or externally, by the environmentally conscious consumers' demands. Thus, in order to proactively respond to these new demands, decision-makers within organisations require up-to-date and accurate performance information that represents the various aspects of their business operations [10–12].

However, due to the complexity of the subject, it can also rely on the level at which the performance is being assessed [13], the agility of the organisation's structure and its elements, which pose additional challenges to evaluating performance [14]. According to Yun and Yigitcanlar [15], organisations that are continuously and consciously altering their business model towards sustainable development can stay competitive. Multiple studies have addressed the sustainable performance of organisations and their willingness to innovate as key

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<sup>3</sup> Z. Sherif, S. Sarfraz, M. Jolly, and K. Salonitis, "Identification of the right environmental KPIs for manufacturing operations: Towards a continuous sustainability framework," *Materials*, 2022.

factors that act hand in hand toward continuous development [16,17]. Another major aspect of continuous development is the organisation's pursuit of value-adding activities to maximise competitiveness [4]. Sustainable development is at the foundation of such a goal, it leads organisations to operate in ways which is less harmful to the environment [18]. This is achieved by considering their resource consumption, which introduces further positive effects on both the cost and the brand image [19].

Among the organisations with the most impact, and definitely, the most impacted is the manufacturing industry. It contributed USD 14.17 trillion to the world's GDP in 2018 and the emission of 24% of global greenhouse gases (GHG) in 2016 [20]. Therefore, sustainable manufacturing has grown into a prominent topic of discussion between business stakeholders around the world. This is attributed to the recognition of the urgency in advancing sustainable manufacturing due to the diminishing non-renewable resources, stricter regulations related to environment and occupational health and safety and increasing consumer preference for environmentally friendly products [21].

It is vital to first define sustainable manufacturing, which is the creation of products that diminish negative environmental impacts while conserving energy and natural resources using economically sound processes that are safe for employees, communities and consumers [22]. It is fair to say that the concept of sustainable manufacturing encourages innovation in production processes and efficiency, thus adding more value to their products and services in favour of cleaner manufacturing [23]. The incentives for manufacturers to pursue sustainability have been researched in depth [24]. It has been reported that those industries implementing sustainable practices cannot only enhance quality but also attain a larger market share [25]. Moreover, manufacturing companies that have fundamentally changed their approach toward more sustainable manufacturing are proven to have consistent positive competitive results [26] despite the need to deliver increasingly customised products and services, with minimum cost and environmental impact [19]. According to a report published in 2021 by McKinsey Global Institute [27], manufacturing industries can get more

positive outcomes on their invested capital by marketing their evolving value streams with minimum environmental impacts and enhancing resource management, such as recycling materials [19,28].

A more pressing matter is the drastic impact that climate change, induced by human actions, has on the world around us. The average temperature is expected to rise at least by 2.4 °C globally in less than a decade [29]. According to the report published by IPCC [30], to maintain the warming below 1.5 °C, we must eliminate carbon emissions by 2050 (Net Zero) and simultaneously reduce emissions by 45% from 2010 to 2030 [31]. In order to deter further shifts in the environment with potentially unforeseeable consequences, many countries have announced greenhouse gas emission reduction plans for the upcoming decades [32]. Therefore, developing sustainable approaches for manufacturing companies has been regarded as a vital global affair [33].

Sustainability has been incorporated into manufacturing management aspects such as process optimisation [34], product development [35,36], supply chain management [37,38], lean manufacturing [39], and supplier evaluation and selection [40]. But none of them focuses exclusively on appraising environmental manufacturing performance [41]. It is clear that the most common view of sustainability stems from the TBL concept. The economic and social aspects are particularly developed, and although the environment is at the core of the sustainability dimension, it is deemed the most lacking aspect [42].

Therefore, the scope of this research is the reporting and analysis of the environmental sustainability of manufacturing systems. The literature reveals multiple attempts made by the researchers in approaching the subject of environmental assessment, such as the considerable body of work on accounting for carbon emissions [43], but it is generally limited to gas emissions based on the GHG protocol [44] or energy consumption [45]. Nevertheless, it should be noted that the aspect of environmental sustainability is concerned with the preservation of the natural basis of life and the security of the ecological conditions of human survival in general [21]. This represents the ability to maintain natural resources and preserve fundamental functions of the

environment over time. Accordingly, considering gas emissions and energy consumption as the only negative impacts in terms of sustainability could be short-sighted [46], and more factors should be considered in any environmental sustainability analysis [47,48]. For instance, global material extraction has grown to more than three times what it was four decades ago while displaying no signs of deceleration and, as a consequence, should be considered [49–51]. According to the review conducted by Contini and Peruzzini [52], the most widely used environmental indicator in manufacturing companies is “energy”, cited by 38 papers, out of 63. However, energy is not the only resource and gas emissions are not the only output. Various sets of key performance indicators (KPIs) are widely available that help define and quantify levels of sustainability in an organisation [53]. However, the recognition of KPIs merely does not allow for an evaluation of sustainability, unless the KPIs are prioritised with a clear assessment model [54].

This study aims to optimise sustainability reporting by developing a framework that allows for the consideration of all environmental indicators with an influence on the manufacturing industry. This includes collecting, ranking, and composing a final KPI set for specified targets. Consequently, the identified KPIs could be utilised as a part of sustainability strategies and projects or as standalone measures for reporting environmental manufacturing. Hence, the framework could aid both targeted evaluations and wider decision-making. The next section presents the literature review conducted as part of the research. Section 3 presents the framework development, followed by its validation in Section 4. Section 5 demonstrates the framework using a case study. Section 6 discusses the results and concludes the paper. Finally, Section 7 identifies limitations along with recommendations for future work.

### **3.3.2 Literature Review**

The literature review sought to build on our understanding of sustainable manufacturing reporting methods and the accompanying factors considered. An examination of the available KPI sets has been conducted, as well as the different methods used to classify them.

### **3.3.2.1 Measuring and Reporting Sustainable Manufacturing Performance**

It is fair to say that the concept of sustainable manufacturing encourages innovation in production systems efficiency, leading to higher-value products in favour of cleaner manufacturing [23]. Therefore, it is evident that there is a need to measure the level of these sustainable practices in favour of economic advantages [55]. More importantly, industry and academia have reached a consensus that both a reduction of emissions of greenhouse gases and an overall promotion of sustainability hold the potential of mitigating or dampening the consequences of climate change. This led to various approaches for analysing and improving the sustainability of these business processes, but these approaches generally limit themselves to a few qualities which they assess (e.g., greenhouse gas emissions or energy consumption) and leave behind many others. Therefore, enterprises need clear methods and guidelines to support decision making by incorporating a system of measurement that addresses the sustainability expectations of both their internal and external stakeholders [12] and to design, operate, manage and fine-tune their manufacturing systems, aiming at environmental objectives to achieve the Eco-economy [19].

Sustainability strategies are the general description given to the methodology or agenda with the purpose of evaluating the impact of organisations' actions. Such strategies are usually composed of a set of KPIs that define and quantify different aspects of an organisation [53]. Clearly defined KPIs are very useful in monitoring and enhancing manufacturing operations [56]. In light of reviewing the literature, the implementation of frameworks has been shown to be essential in maintaining company actions aligned with established strategic goals. Therefore, there is a need to investigate the development of such frameworks and select the right KPIs to facilitate the systematic evaluation of sustainability in order to enhance the decision-making process of the company. Indeed, a robust framework can help decision-makers overcome the challenges of corporate sustainability [57]. Especially if it allows them to better understand their current position and their desired end state. Despite several contributions, many corporations still find it challenging to cultivate and implement sustainability strategies [58].

Sustainability KPIs, indicators or metrics are all different terminologies given to the item of information collected to track the performance of an organisation or system at any operational level that produces output by consuming resources [19]. They form the building blocks of all sustainability strategies. Since the field of sustainability assessment is wide and complex, an increasing number of voluntary initiatives and companies have begun developing and using sustainability KPIs with minimal consideration given to the effect of selecting KPIs on their ability to orient their decision-making process [19].

As a result, an abundance of metric lists and sets exists, which generates confusion among manufacturers as they struggle to select an operational set of KPIs for evaluating sustainability in manufacturing. Specifically, manufacturing companies have been confronted with a decision on which KPIs to select for appraising their processes, and how they should interpret these KPIs in transforming their processes towards a sustainable future [59].

### **3.3.2.2 Sources of KPIs**

As mentioned earlier, sustainability strategies have been vastly formulated and researched extensively. Subsequently, a great variety of KPIs related to sustainability in manufacturing has been developed, identified, specified, analysed and collected in published and restricted sources (patents and internal company documents). The literature review identifies two main sources of sustainability KPIs. The first source includes international bodies and organisations, such as the Organisation for Economic Co-operation and Development (OECD) and the Global Reporting Initiative (GRI) and many more, as listed and reviewed in [60]. These organisations developed general and sector-specific KPIs. The major issue with using such KPIs is that they were developed with the purpose of reporting to external bodies. However, there is a lack of internal reporting guidance for manufacturing organisations and therefore, unsupportive of the decision-making process regarding localised environmental improvements. This revealed the need for a standardised framework for the sustainable manufacturing ecosystem. In this context, a standard methodology for identifying the right set of KPIs with clear definitions is still missing [61].

The second source consists of published research articles with different views and methods on choosing KPIs to include in sustainability strategies. These articles generally developed KPIs or collected and reviewed KPIs from other sources using a wide range of techniques and rationale. A noteworthy contribution can be found in [41], where an attempt was made to integrate sustainability into manufacturing performance by incorporating manufacturing performance KPIs with sustainability KPIs. As a result, a set of core metrics for sustainable manufacturing evaluation was suggested. However, renewable sources or alternative inputs were not considered as they do not directly affect manufacturing performance.

### **3.3.2.3 Sustainability KPIs Classification**

A common category of KPIs is efficiency-based measurements. This includes several important KPIs that aim to assess the efficiency of a process or system based on information concerning the same resource or energy flow from two specific points of the system [43]. It allows its users to obtain a current outlook on the performance but does not necessarily identify specific areas of improvement. Fantini et al. [19] proposed a holistic framework for factories to assess their sustainability readiness by combining production efficiencies, economic performance and environmental impact with respect to time. The suggested framework, along with its developed KPIs, could be used for estimating the current position with respect to established sustainability targets with no possibility of further analysis.

In the same context, to mitigate the need for reviewing multiple sets of indicators, Hristov et al. [62] introduced composite KPIs which combine multiple aspects of system performance into a single measurement, based on a common scientific or economic standard. An example of these KPIs is the Ecological Footprint (EF) which aims to measure how much of the biosphere's annual regenerative capacity is needed to renew the natural resource demand each year. Despite its ability to be used as a stand-alone tool for characterising over-consumption and its wider issues, research around its potential use suggests that the EF does not provide a meaningful demonstration of sustainability. Another common approach

to identifying KPIs is to use the top-down and bottom-up perspectives. KPIs are developed from goals that are defined at a strategic level or specific targets set at an operational level of the production system. Nigri and Baldo [63] explored the use of such a method by developing a questionnaire based on the two perspectives and then ranking the KPIs based on expert feedback. However, the collection method of the KPIs is ambiguous and thus hard to follow. Mien et al. [36] also utilised organisational goals identified by conducting surveys where the most mentioned goals are picked. However, this method eliminated critical reasoning and relied purely on statistical data. The KPIs were then ranked by management for each goal, but again, this can reject some KPIs that might be essential for a different situation, unless the entire method is performed repeatedly.

It seems that the incorporation of methodical sustainability in the organisation's strategy is deficient, as suggested by Yellishetty et al. [35]. Hence, some researchers suggested the use of a set of tools that are not necessarily purpose-built for sustainability but can act as a base or a supportive mechanism for the set of internally defined sustainability KPIs. For instance, industries can use process mapping, such as value stream mapping (VSM), not only for process assessment and development but also for identifying environmental improvement initiatives [63]. Such models can identify which points need to be improved along the production processes. However, because of the potentially large number of manufacturing steps, the application of this methodology (VSM) in an entire company would be very time-consuming, particularly when introducing environmental aspects.

In summary, the literature review presented several KPIs utilised as a part of strategies of environmental analysis for the manufacturing industry. This led to the recognition of the following gaps which this paper will address: (1) Lack of a single set of KPIs that cover all aspects of environmental sustainability, and (2) lack of a framework that incorporates all relevant environmental aspects into the manufacturing industries. This paper presents a structured framework for the

manufacturing industries to identify the right environmental KPIs while addressing the aforementioned gaps.

### **3.3.3 Framework Development**

This section describes the development and utilisation of the proposed framework for environmental manufacturing assessment. It includes building a database for environmental KPIs, identifying, ranking, and composing a final KPIs set for specified targets. With continuous development in mind, further cultivation of the framework is essential for each industry to allow the framework to better match its needs. The proposed approach will also allow for the incorporation of selection criteria that define the usefulness of KPIs in the evaluation process, rather than ranking the KPIs against each other. The framework comprises three stages, as shown in Figure 19.

The purpose of this framework is to provide a guide for the industry to build a database of potential KPIs and identify the right ones for specified objectives. The starting point involves collecting KPIs from available sources. Then the KPIs can be categorised based on environmental goals and manufacturing operations for easy identification. Finally, ranking and prioritising the right KPIs is performed based on a common set of selection criteria.

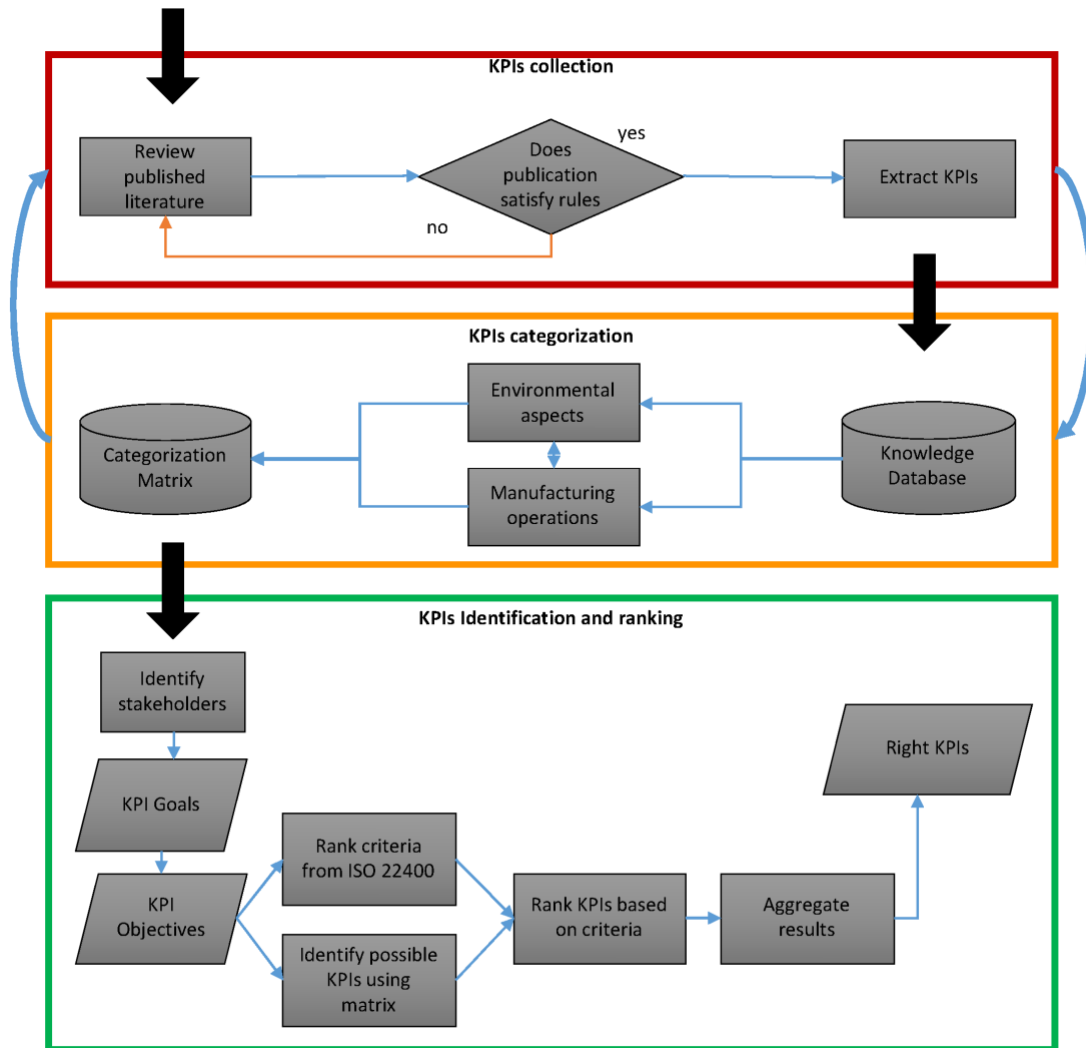


**Figure 19 High-level schematic of the framework**

### 3.3.3.1 Collection of Initial KPIs: KPIs Knowledge Database

The collection exercise performed involves the accumulation of preliminary KPIs and selection criteria which are linked to the KPIs ranking method through a categorisation matrix. The more data is collected over time, the better the environmental analysis process. Sustainability is not a short-term approach to the development of the organisation. Hence, sustainability initiatives should be planned as both short-term and long-term actions to ensure that all stakeholder groups are satisfied [64]. Duflou et al. [65] noted that the selection of KPIs is necessary to assess the performance of a production management system. To build the initial knowledge database, the KPIs are selected from publications under specific conditions adapted from Murad [4]:

- A. Sufficient background research has been conducted before the method introduction
- B. The method should apply to the evaluation of the manufacturing sector
- C. The methodology should be in accordance with the TBL aspects
- D. The KPIs should be chosen or developed systematically with sufficient reasoning
- E. The evaluation method should apply to any stage or type of manufacturing processes

For the KPIs in specific literature to be selected, the publication should satisfy all the rules. Table 7 presents the list of articles selected for the KPIs collection procedure.

**Table 7 Result of analysis of publications presenting sets of sustainability KPIs**

| Title                                                                                                                                  | Rules |   |   |   |   | Selected |
|----------------------------------------------------------------------------------------------------------------------------------------|-------|---|---|---|---|----------|
|                                                                                                                                        | A     | B | C | D | E |          |
| [60] Key Performance Indicators for Sustainable Manufacturing Evaluation in Industry                                                   | y     | y | y | y | y | √        |
| [66] Proposed Framework for Assessing the Sustainability of Membrane Life Cycle                                                        | y     | y | y | y | y | √        |
| [19] Back to Intuition: Proposal for a Performance Indicators Framework to Facilitate Eco-factories Management and Benchmarking        | y     | y | y | y | y | √        |
| [67] Review of Existing Sustainability Assessment Methods for Malaysian Palm Oil Production                                            | y     | y |   |   | y | x        |
| [68] Selection Criteria for Suitable Indicators for Value Creation Starting with a Look at the Environmental Dimension                 | y     | y | y | y | y | √        |
| [4] Metric-based approach to assess sustainable manufacturing performance at manufacturing process levels                              | y     | y | y | y | y | √        |
| [69] How Soft Drink Supply Chains drive sustainability: Key Performance Indicators (KPIs) identification                               | y     | y | y | y | y | √        |
| [62] The adoption of the key performance indicators to integrate sustainability in the business strategy: A five-dimensional framework | y     | y |   |   |   | x        |
| [70] Environmental KPI Selection Using Criteria Value and Demonstration                                                                | y     |   | y |   |   | x        |
| [42] The Role of Sustainability Key Performance Indicators (KPIs) in Implementing Sustainable Strategies                               | y     | y | y | y | y | √        |
| [59] Categorisation of indicators for sustainable manufacturing                                                                        | y     | y | y | y | y | √        |
| [71] Sustainable Value Stream Mapping (Sus-VSM): methodology to visualise and assess manufacturing sustainability performance          | y     | y | y | y | y | √        |
| [72] A Metrics-based Sustainability Assessment of Cryogenic Machining Using Modelling and Optimisation of Process Performance          | y     | y | y | y | y | √        |

Being sustainable means managing processes and resources effectively from a long-term perspective [73]. Therefore, the KPIs collection procedure should be a continuous practice and should be constantly populated with new and up-to-date data by industry experts and managers, leading to a database unique to each organisation. More specifically, they could search for KPIs without relying on rule E. As some KPIs sets can express industry-specific operations, which could be an advantage to identify [74]. Sustainable performance and openness to the innovation of the industries are important requirements for such a continuous development approach [75–77].

### 3.3.3.2 KPIs Categorisation

The size of the KPIs database would mainly depend on the organisation's actions which leads to the possibility of having a large number of KPIs that deal with multiple aspects of manufacturing. However, selecting a small set of KPIs from many of those available for manufacturing operations is often not straightforward. Another issue is the identification of missed aspects that do not have a corresponding metric to analyse. This is mainly due to the complexity of synthesising manufacturing operations and the environmental outlook. As seen from the literature review, despite the efforts made, synchronising the two may not be the easiest task. Therefore, this study tries to address this issue by elaborating on both elements (manufacturing and environment) individually and then combining them into a matrix which allows the categorisation of the collected KPIs. To allow for a full overview of the two elements, each element is divided into two dimensions, vertically and horizontally, as seen in Figure 20.

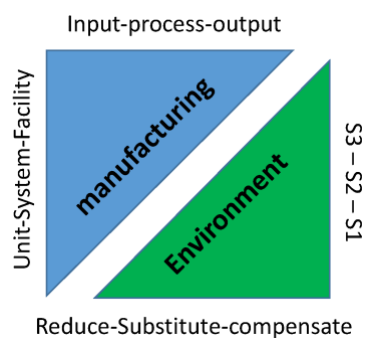


**Figure 20 Categorisation outlook**

Firstly, the manufacturing element can be fairly viewed as an open system horizontally as it includes the exchange of energy and matter in and out of it with certain operations occurring in between. Here, a classification of the operations as input, processes and output was used to sort the collected KPIs [78]. On the other hand, achieving sustainability in manufacturing requires a holistic view spanning not just the product and the manufacturing processes involved in its fabrication, but also the manufacturing system and the entire industry [60]. For that reason, it is most convenient when the considered appraisal for the process level could be expanded to provide a view at a higher level. Hence, the manufacturing operations were divided vertically as follows: unit process, multi-machine system, and facility [65].

Secondly, the environmental element was presented horizontally based on the Institute of Environmental Management (IEMA) GHG management report [79]. It introduced a time-scaled plan of action to reduce, substitute and compensate for resource consumption and the impact of any organisational activities. It aims to help organisations recognise the urgency of their environmental impacts whenever decisions are being made on approaches to sustainable manufacturing. To put the matter in context:

- Reductions: KPIs that deal with real and relative factors with negative environmental impacts that require reduction, till elimination if possible. This includes the most pressing concern of carbon emissions as well as energy and resource management.
- Substitutions: KPIs that reflect on attributes with no further reduction possible, but the negative impact could still be moderated by substituting aspects of the manufacturing operation. This includes the relatively untapped prospective of examining recycling and output reuse.
- Compensations: KPIs which represent any unavoidable or residual emissions, asset sharing, and carbon credits as well as considering actions beyond carbon neutrality.

In terms of a vertical representation, the national grid's scope 1, 2 and 3 of emissions and impact was chosen to represent the environmental KPIs. This is

because it provides a necessary viewpoint on the direct impacts of the organisations' actions, in addition to indirect impacts, which are usually left unconsidered. More specifically, scope 1 deals with impacts from actions that an organisation initiates or controls directly. Scope 2 includes impacts that a company causes indirectly from the production of energy that they then purchase and use. Scope 3 incorporates impacts resulting from other organisations up and down the value chain [80]. In order to combine all the dimensions, a matrix was developed to map the collected KPIs as presented in Table 8. The collected KPIs and the categorisation exercise performed as a part of the study can be found in Table C.2 in 8Appendix C.

**Table 8 KPIs categorisation overview (R: reduction, S: substitution, C: compensation, s: scope)**

|                         | <b>Manufacturing</b><br>→<br>↓<br><b>Environment</b> | <b>Input</b> |   |   | <b>Operation</b> |   |   | <b>Output</b> |   |   | <b>Scope</b> |
|-------------------------|------------------------------------------------------|--------------|---|---|------------------|---|---|---------------|---|---|--------------|
|                         |                                                      | R            | S | C | R                | S | C | R             | S | C |              |
| <b>Operation Levels</b> | Facility                                             |              |   |   |                  |   |   |               |   |   | s1, s2 & s3  |
|                         | Multi-process system                                 |              |   |   |                  |   |   |               |   |   | s1,s2        |
|                         | Unit process                                         |              |   |   |                  |   |   |               |   |   | s1           |

### 3.3.3.3 Ranking of KPIs towards a Specific Goal

The proposed table in the previous section could help in identifying KPIs relevant to the set targets. However, it is possible for a goal to have a few linked KPIs and therefore, it is important to determine which ones to prioritise. This section describes the method to systematically rank candidate KPIs in order of effectiveness towards achieving a specified target. It should allow for an understanding of how the KPIs compare to each other. The final score should represent the degree to which a metric satisfies a set of criteria. As each selection criterion is linked to a defined target, each metric is evaluated for its contribution to the target. Here, the steps involved are (1) identifying goals, (2) identifying stakeholders, (3) stakeholders selecting KPIs, (4) criteria are rated and then (5) KPIs are ranked.

The first step in the ranking of the KPIs is to determine the environmental goal to be reached. Such a goal could represent a generic aim or a target with a specific objective. In addition, the specific KPIs objectives may represent elements of the generalised goal. For the second step, stakeholders with direct ties to manufacturing operations need to be identified. Studies stress that there is value in involving the organisation's main stakeholders in a standardised and authentic manner to become more sustainable, meaning that stakeholders should be at the base of the organisation's strategy [81,82]. Accordingly, the proposed approach involves choosing multiple stakeholders to perform and develop the presented methods of further KPIs collection, categorisation and ranking. Stakeholders include line managers, supervisors, and shop floor workers who will perform the next three steps which represent the ranking calculations.

The ranking method suggested in this paper aims to evaluate the different KPIs collected and categorised. Kibira et al. [83] stated that the effectiveness of KPIs in representing a goal is assured by defining a set of selection criteria that the KPIs should follow. Nevertheless, not all the criteria are of equal influence on the KPIs and for that reason, the proposed method incorporates a set of criteria into the ranking procedure.

Donaldson and Preston [81] suggest that the criteria should be gathered from the literature, but this could lead to a discursive list. ISO 22400 offers a set of criteria that represent the usefulness of operational KPIs in a manufacturing setting along with their definitions. Eighteen criteria are extracted from the ISO document as listed in Table 9. Each criterion represents a characteristic that a KPI should be or have. Therefore, each one of the criteria is assigned a score ranging from 0 (not important) to 5 (very important) based on how important these attributes are to the KPIs in terms of dealing with the targets in question. This score is represented as  $C_i$ . Stakeholders then select the KPIs corresponding to these targets using the knowledge database. The KPIs are then scored based on how well they satisfy each criterion on a scale of 0 (not satisfied) to 5 (completely satisfied), noted as  $K_i$ . Finally, to produce a final score for each KPI, the score of

each criterion,  $C_i$ , is multiplied by the score of the KPI for this criterion,  $K_i$ . this is expressed by:

KPI final score is computed using the following:

$$\sum_{i=1}^n C_i(K_i)$$

where the KPIs with higher scores are considered more effective in representing the goal identified at the start. Subsequently, the stakeholders can determine a cut-off point for the scores and only consider the consequent KPIs.

**Table 9 Criteria extracted from ISO 22400**

|            |                |              |
|------------|----------------|--------------|
| Accurate   | Automated      | Complete     |
| Actionable | Buy-in         | Documented   |
| Aligned    | Comparable     | Inexpensive  |
| Timely     | Understandable | Standardised |
| Trackable  | Valid          | Unambiguous  |
| Predictive | Quantifiable   | Relevant     |

This methodology agrees with the contingent theory that advocates the unavailability of a single right answer [84] but identifying the optimum course of action is dependent upon the circumstances of each organisation. Following such theory, it allows the method to be both systematic in nature yet agile enough to be utilised in many situations.

### 3.3.4 Framework Validation

To validate the developed framework, two sustainable manufacturing experts were presented with the steps involved in collecting and categorising environmental KPIs, together with the procedure to rank indicators based on their effectiveness in representing a specified target. Using the following set of statements, the developed framework was quantitatively assessed by rating each statement on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree):

- Categorisation successfully integrates environmental sustainability in manufacturing operations
- Criteria aid in choosing KPIs by representing their usefulness/effectiveness
- Ranking results would support decision making by prioritising KPIs
- The framework has potential applicability in manufacturing organisations
- The approach is user-friendly

Where the first three statements are specific to the elements of the framework while the last two represent a more general overview of the applicability and usage of the framework. The results are plotted in Figure 21.

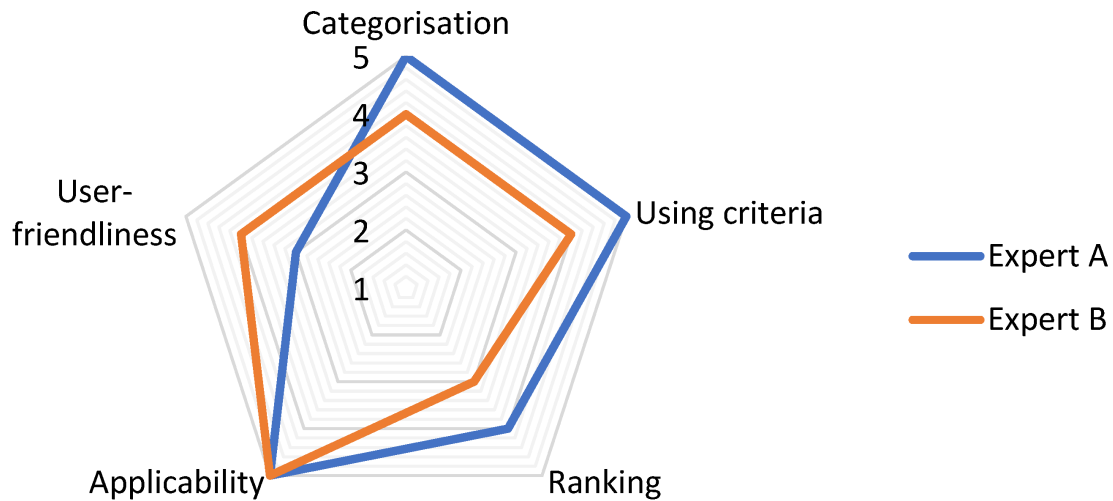


**Figure 21 Validation results**

Overall, the results indicate a positive stance on the developed framework. More specifically, the potential applicability of the framework has been corroborated by both experts. Moreover, the continuous approach for collecting and categorising KPIs to allow for creating a unique database for each organisation has been acknowledged positively. However, minor remarks were made on the user-friendliness of the ranking method as it is not instantly intuitive but requires a thorough explanation.

### 3.3.5 Framework Demonstration

Using a manufacturing case study, this section investigates the viability of the procedure described earlier for identifying the right KPIs. This includes analysing

the knowledge database built as a part of this research as well as testing the proposed ranking method.

To accomplish this, informal interviews were conducted with experts from two glass industry companies, denoted as companies A and B. First, open questions were asked to grasp their current environmental assessment methods, and any indicator sets they utilise. Second, their input was acquired on the framework by presenting the different steps involved. Additionally, a case study was performed for the ranking process using a target the interviewee chooses. This allowed for identifying possible benefits and limitations. For the ranking stage, the interviewees were asked to select a goal from the following options which were based on operational goals from several manufacturing industries:

- Reduce energy use
- Zero waste to landfill
- Reduce gas emissions
- Increase renewable electricity

Then, they assigned an importance level for some criteria they deemed immediately crucial. The next step was for them to identify possible KPIs using the Knowledge database and rank them using the method described in 3.3.3.3.

#### **3.3.5.1 Case Study**

Company A indicated that they rely on qualitative methods that do not incorporate KPIs while deciding on environmental sustainability actions. On the other hand, company B stated that KPIs are a big part of their environmental plans based on the TBL paradigm with a focus on legal compliance. However, they are usually developed for specific projects and only cover individual aspects concerning the project with no procedure in place to select, record or classify them. Accordingly, they both expressed appreciation for building a database with a categorisation method that focuses on manufacturing operations.

To perform the ranking stage, company A selected reducing energy at the process level as their target while company B selected increasing renewable electricity at a facility level. Table 10 and Table 11 present the ratings assigned

by the interviewees of companies A and B, respectively, for the selected KPIs for each criterion and the calculated final score of each KPI.

**Table 10 Case study result of company A. Target: reduce energy use**

|   |              | KPIs              |                  |                         |              |                         |
|---|--------------|-------------------|------------------|-------------------------|--------------|-------------------------|
|   | Criteria     | Energy efficiency | Fuel consumption | Electricity consumption | Energy waste | Fossil fuel consumption |
| 4 | Accurate     | 4                 | 4                | 5                       | 3            | 5                       |
| 3 | Trackable    | 2                 | 4                | 5                       | 2            | 4                       |
| 2 | Quantifiable | 4                 | 5                | 5                       | 5            | 5                       |
| 1 | Inexpensive  | 3                 | 3                | 5                       | 4            | 4                       |
|   | Final Score  | 33                | 41               | 50                      | 32           | 46                      |

**Table 11 Case study result of company B. Target: increase renewable electricity**

|   |              | KPIs             |                       |
|---|--------------|------------------|-----------------------|
|   | Criteria     | Renewable Energy | Renewable electricity |
| 4 | Trackable    | 5                | 5                     |
| 3 | Inexpensive  | 2                | 2                     |
| 2 | Timely       | 3                | 3                     |
| 1 | Quantifiable | 4                | 5                     |
|   | Final Score  | 36               | 37                    |

For company A, the results revealed that the KPIs are ranked as follows: (1) electricity consumption, (2) fossil fuel consumption, (3) fuel consumption, (4) energy efficiency and (5) energy waste. The industry expert then elected 40 as the cut-off point and identified the top 3 KPIs to be the right ones for measuring the target out of the selected KPIs. For company B, only two KPIs were found relevant to the goal which implies a lack of KPIs aimed at renewable energy management in the database.

### 3.3.6 Discussion and Conclusions

In this paper, a framework of environmental KPIs selection for manufacturing industries has been presented. Numerous studies stressed the significance of implementing eco-friendly activities on both profitability and assisting in the mitigation of irreversible environmental circumstances. Nevertheless, several

sustainability assessment methods that feature KPIs have been reported in the literature with minimal emphasis on covering all manufacturing aspects that impact the environment.

The work started by collecting KPIs from published articles that satisfy a set of rules to ensure their appropriateness. The collected indicators were then categorised based on the environmental aspects and the manufacturing operations. To discover the usefulness of the different KPIs, a ranking method was introduced that includes selection criteria in the final score of each KPI. Then, using a quantitative survey, the framework was validated by subject matter experts. Finally, the viability of the framework has been investigated using a manufacturing case study to practically ascertain its benefits and reveal any limitations. The framework was accepted by both subject matter and industry experts as means to categorise KPIs and evaluate their effectiveness. More specifically, the categorisation method showed its capability to embrace aspects of both manufacturing operations and environmental sustainability. Additionally, it aided in choosing KPIs and in identifying areas that lack monitoring. Incorporating selection criteria assisted in identifying the most effective KPIs for a specified goal. It was pointed out by one of the participants that the ranking process is particularly helpful with identifying the right KPIs between a list of indicators with similar emphasis as well as supporting decision-making by prioritising KPIs.

### **3.3.7 Limitations and Future Research**

While the framework has been validated as a step towards enabling manufacturing industries to build, embed and sustain a strategic organisational approach to environmental manufacturing, it is limited in some respects. Theoretically, the method is limited by the research available on the subject which constrains the possible number of KPIs that could be collected and categorised. Furthermore, the method is limited practically by the collection exercise that should be performed as part of the framework. In the case of the database built as part of the research, it is limited to the genericness of the initially collected indicators. Both companies involved in the case study have stated their interest

in using the categorisation method with a collection of industry-specific KPIs. In the case of the glass industry, this could include indicators such as cullet utilisation and reuse of collected dust [85,86]. This leads to the next research step which involves further building the knowledge database with the aim of collecting KPIs that fulfil the underacknowledged categorisation sections. For instance, operations substitutions could include indicators representing the introduction of environmentally positive processes to an existing system such as biomethanisation and carbon capture as suggested by one of the industry experts. Further work might aim to investigate the utilisation of the identified KPIs with an indication of how to achieve specified targets by using those KPIs.

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### **3.4 Contribution of Papers to Thesis Objectives**

The two papers in this chapter make complementary contributions toward fulfilling Objective 2 by enabling the structured and conscious definition of environmental KPIs for sustainability in manufacturing.

The first study contributes through empirical investigation. It reveals how energy-related KPIs were applied across sectors, identified inconsistencies in metric selection, and evaluated their performance using ISO 22400 criteria. It also highlighted variation in data collection practices and benchmarking maturity, based on case studies from foundries and other industrial processes. While the focus was on energy metrics, the findings offered broader insight into how sustainability metrics were defined, selected, and applied in practice.

The second paper addressed the methodological gap by introducing a structured framework for KPI selection, supported by a multi-dimensional categorisation system and a goal-oriented ranking approach. It classified environmental KPIs based on themes (reduction, substitution, compensation), operational levels (process, system, facility), and emission scopes (1, 2, and 3). Although the method was developed for environmental indicators, the framework's level-based structure and metric database are applicable to other sustainability dimensions, including economic and social aspects. Validation was conducted through expert review and a case study involving two glass manufacturers, demonstrating both flexibility and relevance.

Together, the papers:

- Establish a clear industry-informed perspective on the use and limitations of current metrics.
- Provide a replicable methodology for building KPI databases and assessing metric effectiveness.

These contributions laid the foundation for the benchmarking and similarity-based assessments developed in the subsequent chapters. They advance the thesis's aim of implementing sustainability metrics in a way that is adaptable, practical and scalable across sectors.

## **4 Benchmarking High-Impact Manufacturing Processes for Energy and Emissions**

### **4.1 Papers Linkage to Research Aim and Objectives**

This chapter addresses Objective 3, which is to enhance process-level efficiency by evaluating intensive processes, identifying resource optimisation opportunities and proposing actionable benchmarking approaches. It contributes to this goal through two interrelated studies that develop and apply process-level benchmarking methods within energy- and emission-intensive manufacturing systems.

The first paper focuses on cross-sectoral energy mapping and performance analysis across the foundation industries. It builds a systems view of energy drivers using causal loop diagrams and benchmarks current process performance against BATs, research innovations and theoretical minimums. This allows the identification of inefficiencies and sector-specific constraints that limit improvement potential.

The second paper deepens this analysis through a detailed case study of a UK cement plant. It introduces a structured benchmarking approach for energy consumption and CO<sub>2</sub> emissions, combining intensity and performance metrics with a comparative analysis of best practice adoption. The approach also considers economic feasibility to support practical implementation.

Together, these studies provide a robust empirical and methodological foundation for process-level benchmarking. They highlight both the scale of efficiency gaps and the actionable opportunities available to industrial actors.

## **4.2 Investigating Energy Consumption Drivers and Reduction Measures in Key Manufacturing Sectors <sup>4</sup>**

### **4.2.1 Introduction**

Energy consumption is a critical determinant of both the environmental sustainability and economic viability of manufacturing industries. As global efforts intensify to achieve carbon neutrality, the role of industrial sectors in driving energy demand and emissions has come under increasing scrutiny. Manufacturing industries, particularly those reliant on high-temperature processes, remain some of the largest energy consumers worldwide. These industries face mounting pressure to balance economic growth with sustainable practices, necessitating a detailed understanding of energy usage patterns, drivers, and opportunities for efficiency improvements. The cement, glass, ceramics and steel industries are foundational to global economies due to their essential contributions to numerous downstream industries, including construction, infrastructure and advanced technological applications such as electronics, renewable energy systems, aerospace components, and high-performance materials for manufacturing [1,2].

However, the significant energy demands of these industries drive substantial operational costs and greenhouse gas emissions [3]. Energy consumption in manufacturing processes is therefore both a critical economic factor and a major contributor to global environmental challenges. Cement production alone, driven by the energy-intensive calcination process, accounts for about 7% of global CO<sub>2</sub> emissions [4]. Similarly, steel manufacturing, with its reliance on blast furnaces, is responsible for approximately 8% of global CO<sub>2</sub> emissions [5] and a comparable share of global industrial energy demand [6]. The urgency to improve energy efficiency in these sectors is underscored by both economic and environmental imperatives, as industries face growing pressure to reduce costs and minimise their carbon footprint [7,8].

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<sup>4</sup> Z. Sherif, S. Sarfraz and K. Salonitis, "Investigating energy consumption drivers and reduction measures in intensive manufacturing sectors", 2025 (To be submitted).

Despite extensive research on energy-saving technologies, gaps remain in understanding the key drivers of energy use and aligning reduction strategies with sector-specific needs [9,10]. Numerous studies advocate using energy thresholds as benchmarks to guide process improvements, with theoretical and practical best practices providing a foundation for energy efficiency strategies [11,12]. Research suggests that many industrial operations consume at least 50% more energy than the theoretical minimum, highlighting significant opportunities for optimisation [13]. While broad energy bandwidth studies by institutions such as the U.S. Department of Energy offer valuable insights, they often lack granularity in identifying process-specific improvements [14]. Existing energy consumption benchmarks often rely on outdated data and focus primarily on conventional technologies, overlooking the impact of emerging innovations. Furthermore, the relationship between energy-saving measures and the specific factors influencing energy consumption remains underexplored, limiting the effective implementation of efficiency strategies.

The goal of this research is to bridge these gaps by conducting a structured analysis of energy consumption patterns in the cement, glass, ceramics and steel industries. This is achieved by integrating a detailed examination of the factors influencing energy use in the most energy-intensive processes across these sectors with an assessment of energy consumption thresholds that benchmark current practices against theoretical and practical energy targets. The thresholds are updated using the latest data and account for advancements in existing and emerging technologies. By combining these analyses, the study offers a comprehensive procedure for improving energy efficiency in critical industrial sectors. It provides stakeholders with actionable guidance to prioritise energy-saving measures that address the most significant inefficiencies, while also offering researchers a replicable methodology and identifying underexplored areas for further innovation. Ultimately, this work supports efforts to reduce resource consumption and carbon emissions in energy-intensive industries, directly contributing to the United Nations Sustainable Development Goals (SDGs) on responsible consumption and production (SDG 12) and climate action (SDG 13) [15,16].

#### **4.2.2 Literature Review**

The cement, glass, ceramics, and steel industries are among the most energy-intensive manufacturing sectors, contributing substantially to global energy demand and associated greenhouse gas emissions. These sectors depend on high-temperature processes such as clinkerisation in cement, melting in glass, firing in ceramics, and ironmaking in steel, all of which rely heavily on fossil fuels as the primary energy source [17]. Consequently, they face growing economic and environmental pressures to reduce energy consumption and improve process efficiency.

Despite differences in process configurations and end products, these industries share several common challenges. High heat losses through combustion, radiation, and exhaust gases remain a widespread issue across all four sectors, even in modern plants with upgraded technologies [18–20]. While advancements such as preheater kilns in cement, regenerative furnaces in glass, and heat recovery systems in ceramics and steel have improved energy efficiency, insulation performance, process control, and equipment degradation continue to limit overall gains [21,22]. Material inputs also play a significant role, with raw material characteristics such as moisture content, particle size, and chemical composition influencing energy demand during transformation and processing [23,24]. At the same time, sector-specific differences impact how energy is used and where the greatest efficiency gains can be made. For instance, cement production requires intense thermal input for the calcination of limestone, while glass manufacturing is more sensitive to the quality and proportion of cullet in the melt. In ceramics, energy intensity is shaped by tile formulations and firing cycles, whereas in steel, the energy profile is strongly influenced by the type and quality of reductants used in the blast furnace. Nonetheless, core drivers such as equipment performance, fuel type, plant scale, and process control remain critical across all four sectors [25,26].

Efforts to reduce energy use have included a wide range of strategies, from process optimisation and fuel substitution to the adoption of waste heat recovery (WHR) systems [27,28]. WHR is particularly relevant in high-temperature

operations like cement and steel production, where repurposing excess heat from kilns and furnaces can yield significant energy savings. In the cement industry, for example, WHR can reduce thermal energy demand by 0.21–0.22 GJ per tonne of clinker and electrical energy consumption by up to 22 kWh per tonne [29,30]. More recently, energy reduction strategies have become increasingly tied to decarbonisation roadmaps. Technologies such as electrified furnaces, hydrogen injection, and synthetic fuels are now being explored and adopted, primarily to reduce CO<sub>2</sub> emissions [31–33]. These solutions may also deliver energy savings through improved combustion or material efficiency, but their implementation often involves high capital costs, infrastructure constraints, and uncertain long-term performance [34,35]. In many cases, these technologies are introduced without first optimising existing energy baselines, which can undermine their effectiveness and reduce their return on investment.

While many of these efforts show promise, several important research gaps remain. A key limitation is the lack of integration between energy-saving measures and the specific process-level factors that drive energy consumption. Existing studies often focus on isolated technologies without analysing how material, operational, and environmental variables interact to affect energy demand [25,36,37]. Furthermore, although energy consumption thresholds have been proposed, many of these benchmarks rely on outdated data, general assumptions, or sector-wide averages that fail to capture emerging innovations and process-specific variations [1,12,14]. This limits their value in guiding targeted improvements and obscures the full potential for optimisation.

Addressing these gaps is essential to ensuring that energy efficiency strategies are technically sound, economically viable, and aligned with broader sustainability objectives. This study contributes to that goal by systematically analysing energy consumption drivers and thresholds in the cement, glass, ceramics, and steel industries. It offers a methodology for linking process-level inefficiencies with actionable energy-saving measures and supports more robust benchmarking of performance across sectors.

### 4.2.3 Methodology

This study employed a mixed-methods approach to comprehensively analyse energy consumption in the cement, ceramics, glass, and steel sectors. The rationale for this approach stems from the complex nature of industrial energy use, which is shaped by the interplay of technical, material, and operational factors. To capture this complexity, the methodology integrates both quantitative benchmarking and qualitative systems analysis, offering a dual perspective on performance assessment and efficiency improvement.

The analysis began with detailed process mapping to identify unit operations and estimate their energy consumption shares, as illustrated in Figure 22. This established a baseline for evaluating sectoral performance and served as a foundation for two complementary lines of analysis. One line focused on developing energy consumption thresholds by reviewing current industrial practices, identifying best available technologies (BATs), emerging research and development technologies (R&D), and incorporating theoretical minimums. These thresholds enabled a structured benchmarking of energy efficiency across processes and sectors.

The second line of analysis examined the underlying drivers of energy use. Influencing factors were identified, categorised, and contextualised across processes, including configurations, material inputs, fuel types, and operational controls. To explore how these factors interact and affect energy outcomes, the study developed causal loop diagrams (CLDs). These diagrams provide a visual synthesis of interdependencies and feedback, offering a systems-level view of energy performance and highlighting leverage points for intervention.

The research is based entirely on secondary data obtained from a structured review of peer-reviewed literature, industrial reports, energy benchmarking studies, and technical publications. This literature provided the quantitative values, thresholds, and factor insights that underpin both strands of analysis. Together, the threshold benchmarks and CLDs form the core outputs of the methodological framework, enabling a robust, cross-sectoral evaluation of industrial energy efficiency.

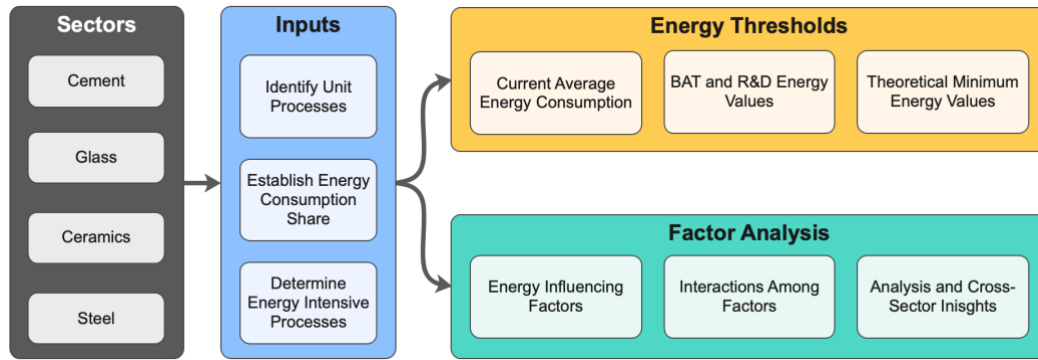


**Figure 22 Methodology overview linking process mapping to two complementary outputs. Energy thresholds and energy influencing factor analysis**

#### **4.2.3.1 Production Process Mapping**

A structured approach was employed to map the manufacturing processes of key products in the cement, glass, ceramics, and steel industries. This involved an analysis of each process, with a specific focus on thermal and electrical energy usage alongside Scope 1 emissions. In this context, thermal energy refers to the heat required for high-temperature operations such as kilns, furnaces, and sintering, while electrical energy refers to the power consumed by mechanical and auxiliary equipment such as motors, grinders, fans, and pumps. The mapping exercise was essential to identify the most energy-intensive processes within each sector while establishing an understanding of the core elements that may impact the consumption. Moreover, to ensure consistency, only Scope 1 emissions are reported. These include fuel combustion and raw material decomposition. Electrically driven processes such as grinding, annealing, and rolling are excluded, based on the assumption that electricity is purchased (i.e., Scope 2). Additionally, it is assumed that thermal energy is generated primarily through fossil fuel combustion rather than alternative sources such as biomass.

The analysis boundary is illustrated in Figure 23. Data collection covered all major processes from raw material preparation through processing and transformation to the final finishing stages. The analysis excluded the extraction of raw materials and subsequent stages such as product packaging and shipping. This focused scope ensured that the study provided a detailed understanding of the core manufacturing stages and their associated energy demands.

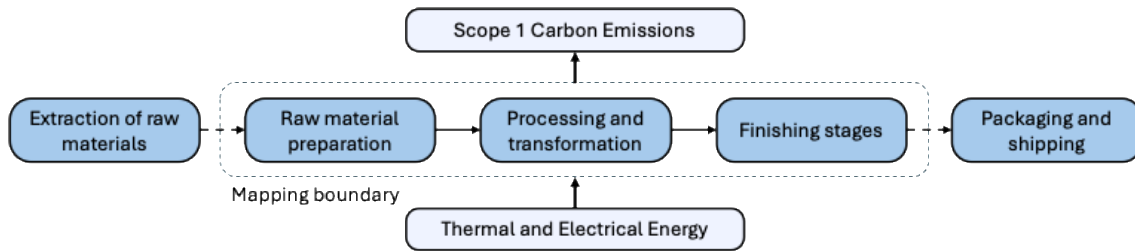


**Figure 23 Process boundary for manufacturing analysis, highlighting the stages from raw material preparation to finishing stages**

#### 4.2.3.2 Influencing Factors

Factors influencing energy consumption in the most energy-intensive processes of the glass, ceramics, steel, and cement sectors were identified through a review of the literature and subsequently classified into six categories (defined in Table 12), namely Energy Input, Material Input, Equipment, Operational Management, and Environmental factors. This classification captures the diverse dimensions of energy consumption by organising factors across technical and operational drivers, enabling a holistic analysis of their interrelationships.

**Table 12 The definitions of influencing factors categories**

| Category       | Definition                                                                  |
|----------------|-----------------------------------------------------------------------------|
| Energy Input   | Factors contributing to direct energy input or aiding energy generation     |
| Material Input | Attributes of input materials, such as composition and flow rate            |
| Equipment      | Elements related to machinery upgrades, subsystems, or operating parameters |
| Operational    | Strategies for managing production systems and converting inputs to outputs |
| Environment    | The immediate surroundings affecting equipment or processes                 |

The categorisation methodology, adapted from the generic manufacturing process model proposed by the author of the present study in a previous paper [37], serves to structure and compare factors from different literature sources. Grouping similar factors also helps identify patterns and trends, providing a more structured basis for analysis.

To explore the interactions between the identified factors, CLDs were developed. This approach was selected because it captures both direct and indirect links among factors and can highlight potential causal relationships and

interdependencies [40]. CLDs systematically map how one factor can influence another, either directly or through intermediate variables, providing a dynamic view of energy consumption [41]. By visualising feedback loops and identifying leverage points, the diagrams reveal where targeted interventions could deliver meaningful energy savings [42,43]. The relationships identified in the CLDs were based on factor analysis studies, energy consumption patterns, and operational parameters reported in the literature. To ensure that indirect influences could also be examined, broader operational parameters, such as production rate, were included in the analysis.

#### 4.2.3.3 Thresholds

A threshold analysis was conducted to benchmark energy consumption in the most energy-intensive processes. Four key thresholds were defined, namely, the current industrial average, BAT, emerging R&D solutions, and the theoretical minimum, as illustrated in Figure 24.

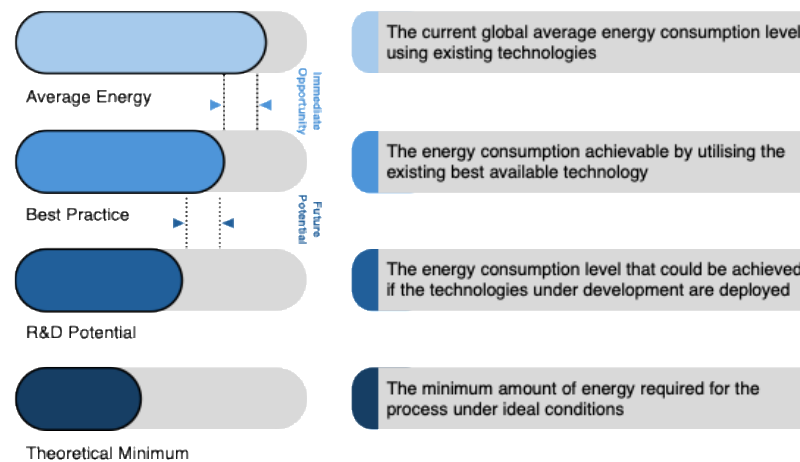


**Figure 24 Energy consumption thresholds, illustrating the progression from the global average (current technologies) to the theoretical minimum, with intermediate benchmarks for best available technologies (BAT) and emerging research and development (R&D) advance**

These thresholds were chosen to represent the full spectrum of energy consumption, from current industrial practices to theoretical ideals. The distinctions between these thresholds provide valuable insights into the nature of these opportunities. The gap between the average and best practice thresholds

highlights the potential for efficiency gains through existing technologies, while the difference between best practice and R&D potential reflects advancements achievable through emerging innovations. Together, these thresholds identify opportunities for both short-term improvement and long-term development and innovation potential. For each sector, the BAT with the highest energy saving impact was used to define the upper limit of current practice, and the most promising R&D technology was selected to represent the frontier of innovation. This approach enables a clear comparison between established solutions and future developments, helping to bridge the gap between immediate gains and long-term energy efficiency goals.

#### **4.2.3.4 Literature data collection procedure**

As previously stated, the inputs of this research, including energy influencing factors, energy saving measures and energy thresholds, were derived by collecting data from the literature on the cement, ceramics, glass, and steel sectors. The search involved defining research objectives, selecting precise keywords, and conducting database searches in Scopus, Web of Science, and Google Scholar. Studies were screened and evaluated for quality and relevance. Only peer-reviewed journal articles and conference papers in English published since 2010 were considered, with emphasis on literature from 2015 onward to capture recent technological developments. No geographical restriction was applied to allow for a global viewpoint. This structured approach ensured that the literature used directly supported the objectives of the study. Applicable data were extracted and organised into thematic categories, including process mapping, influencing factors, and technological advancements.

#### **The keywords used for the data collection are summarised in**

Table 13 and grouped according to their purpose, such as process mapping, factor identification, BATs, R&D technologies, and theoretical minimum thresholds. Synonyms were incorporated to improve coverage, and searches were applied independently to each sector to ensure comprehensive retrieval of sector-specific literature.

**Table 13 Keywords used in the literature review, categorised by specific objectives**

| Objective           | Keywords                                                                   |
|---------------------|----------------------------------------------------------------------------|
| Process Mapping     | "Manufacturing", "Map", "Energy", "Emissions", "Equipment" and "Materials" |
| Factors             | "Energy Consumption", " Factors" And " Influence"                          |
| BATs                | "Best Available Technology" And " State-Of-The-Art"                        |
| R&D Technologies    | "Emerging", "Future Technologies" And "Feasibility"                        |
| Theoretical Minimum | "Minimum", "Theoretical" And "Ideal Energy"                                |

#### **4.2.4 Results and Discussion**

This section presents the results of the sectoral analysis conducted for the cement, glass, ceramics and steel industries, with a specific focus on the most energy-intensive processes within each sector. The findings highlight key factors influencing energy consumption, their interdependencies, and the opportunities for improvement through targeted interventions. Furthermore, the results emphasise how process-specific energy consumption thresholds provide actionable benchmarks, offering both immediate and long-term pathways for optimisation and innovation.

##### **4.2.4.1 Production Mapping**

Understanding energy consumption patterns in manufacturing processes is critical for identifying efficiency opportunities. This section examines the production mapping of cement, ceramics, glass, and steel, highlighting the energy-intensive stages within each sector (Figure 4). Despite sectoral differences, common trends emerge, particularly in the reliance on high-temperature processes, extensive thermal energy use, and CO<sub>2</sub> emissions associated with both fuel combustion and material decomposition.

Cement manufacturing (Figure 25.a) is dominated by clinkerisation, which alone accounts for 99% of thermal energy consumption and 97.5% of the carbon emissions. The process begins with quarrying and raw meal preparation, followed by grinding and drying before entering preheater cyclones and a calciner, where

limestone undergoes calcination at around 1450°C, releasing process emissions from carbonate decomposition. The rotary kiln is the most energy-intensive stage, followed by clinker cooling and final grinding. Dual source CO<sub>2</sub> emissions from fuel combustion and raw material decomposition make clinkerisation a prime target for energy efficiency improvements [44–47].

Glass manufacturing (Figure 25.b) is overwhelmingly driven by the melting stage, which accounts for 96% of thermal energy use and 79% of total CO<sub>2</sub> emissions. The process starts with batch preparation, after which materials are heated above 1500°C to form molten glass. Maintaining this temperature requires continuous high-temperature operation. Annealing follows as a controlled cooling step to ensure structural stability [48,49].

Ceramic tile manufacturing (Figure 25.c) consists of crushing, spray drying, forming, glazing and firing. Among these, firing is the dominant energy-intensive stage, consuming 64% of thermal energy and contributing to 49% of CO<sub>2</sub> emissions. Kilns operate at 1000–1300°C, primarily using natural gas. Spray drying is the second most energy-intensive stage, accounting for 36% of thermal energy use. Unlike cement production, where the calcination process is the primary emissions source, the ceramics industry's emissions are driven mainly by fuel combustion, with minor contributions from raw material decomposition [50,51].

Steel manufacturing (Figure 25.d), particularly through the blast furnace–basic oxygen furnace (BF BOF) route, is the most energy-intensive of the four sectors. Ironmaking in the blast furnace dominates thermal energy use, with coke serving as both the primary fuel and reducing agent. This stage alone accounts for 66% of thermal energy consumption and 45% of sectoral emissions. Steelmaking in the BOF is exothermic but still generates emissions from the oxidation of carbon impurities. Downstream processes such as rolling, particularly hot rolling, represent the highest electricity demand, similar to final grinding in cement and finishing operations in glass production [52,53].

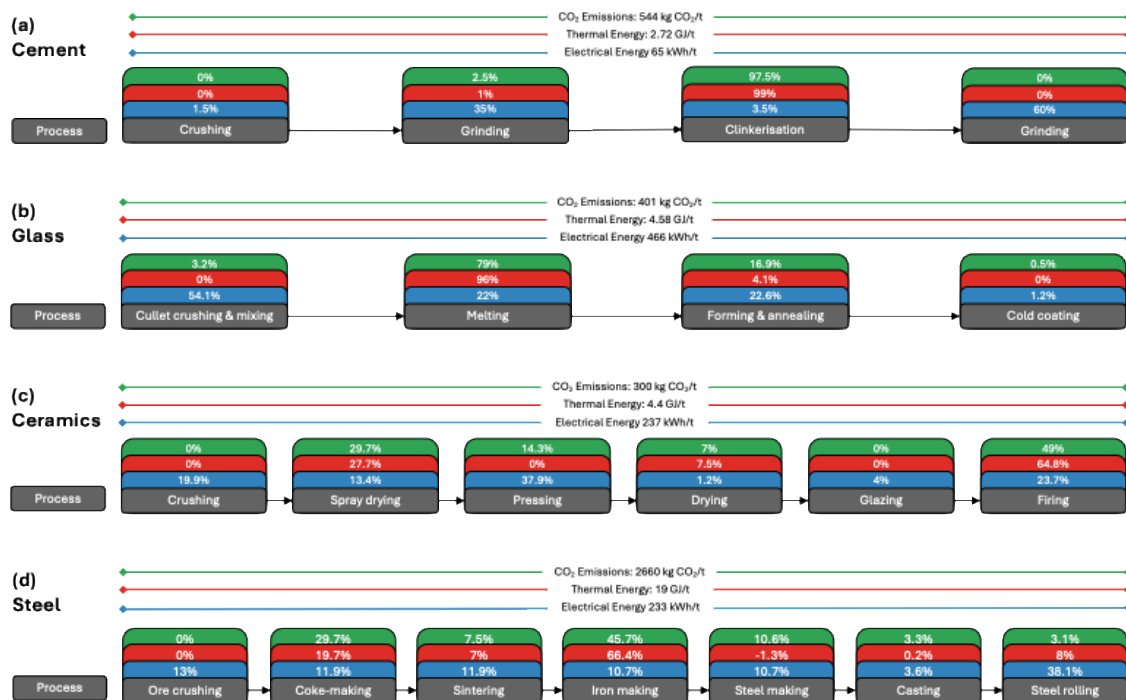


**Figure 25** Process maps of cement, glass, ceramics, and steel production, developed in this study using data from the literature. The maps illustrate raw material preparation, processing and transformation, and finishing for a) cement [44–47], b) glass [48,49], c) ceramics [50,51] and d) steel [52,53]

Despite differences in products and raw materials, the cement, ceramics, glass, and steel industries share core energy challenges. All four sectors rely on high-temperature processes typically operating above 1000–1600°C. Thermal energy demand is largely driven by fuel combustion, using mixed fossil fuels [54], natural gas dominating in ceramics and glass [55,56], and coke serving as both fuel and reductant in steel [57]. Material properties further influence energy use. Carbonate decomposition in cement, ceramic sintering, cullet content in glass, and iron ore quality in steel all affect the intensity of thermal processes. These shared dependencies highlight the need for cross-sector strategies such as alternative fuels, process electrification, and waste heat recovery to achieve significant energy and emissions reductions. The most energy-intensive processes are summarised in Figure 26.

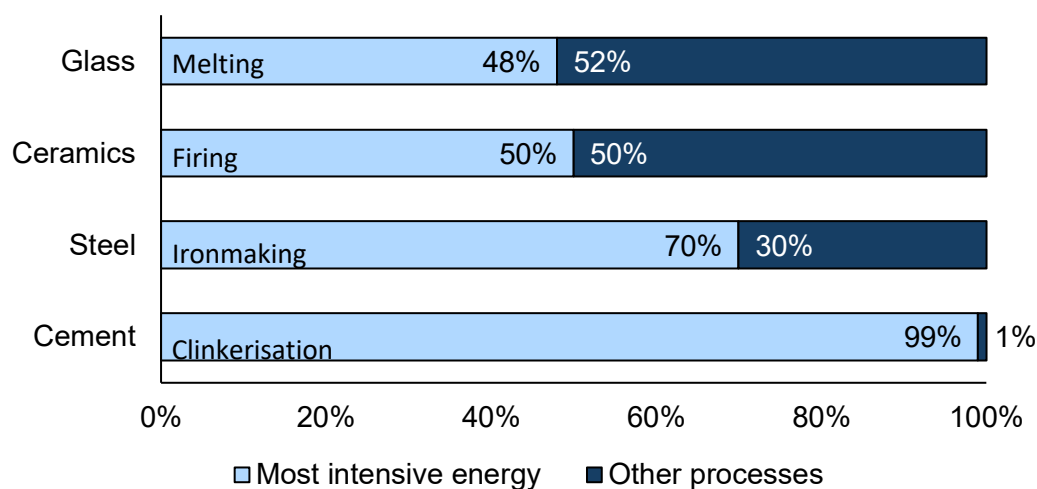


**Figure 26 Intensive processes and their energy consumption share in comparison to all other processes across the four sectors**

#### 4.2.4.2 Influencing Factors

Energy consumption in manufacturing processes is influenced by material inputs, energy inputs, equipment performance, operational practices, and environmental conditions. Each category affects energy use in different ways, from the thermochemical properties of raw materials to the efficiency of combustion systems and the stability of process control mechanisms. While sector-specific variations exist, common drivers are observed across cement, ceramics, glass, and steel, revealing inefficiencies and potential areas for energy savings.

Following the collection of influencing factors from the literature, CLDs were developed to represent the interactions between them and identify interdependencies. To enrich the analysis, process efficiency and production rate were also incorporated into the CLDs alongside the primary influencing factors. Efficiency captures how effectively energy is converted into useful output per unit of product. This parameter highlighted situations where energy use improves in quality, even if total consumption remains the same or increases due to higher throughput. Production rate provided a broader operational perspective, as higher production volumes can offset unit-level efficiency gains by raising total energy demand, while lower utilisation can reduce overall efficiency. Including these parameters ensured that the CLDs capture both how energy is used and

how operational conditions affect total demand, enabling a more comprehensive understanding of where optimisation strategies can have the greatest impact.

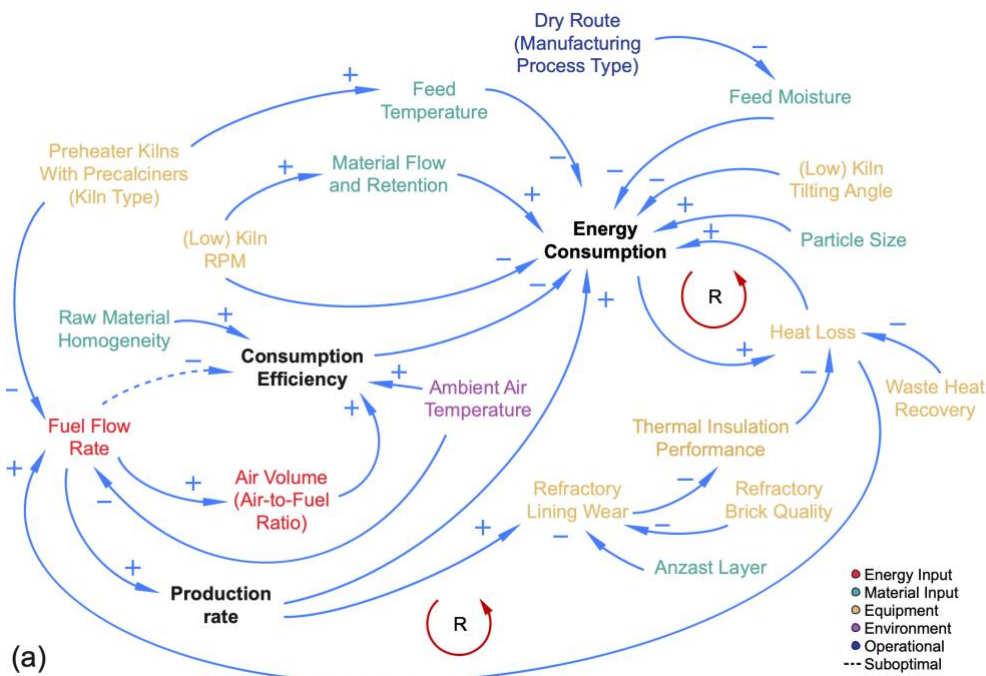
Understanding the interdependencies between influencing factors is critical for identifying key drivers of energy consumption and efficiency losses across manufacturing sectors. The CLDs presented in Figure 27 provide a visual representation of these interactions for (a) clinkerisation, (b) glass melting, (c) ceramics firing and (d) ironmaking. These diagrams illustrate the feedback mechanisms that either amplify energy inefficiencies (-) or counteract them (+), offering insights into how different factors contribute to overall energy consumption. Across all four sectors, three key feedback pathways emerge.

The first relates to material properties. Moisture content, feed composition and particle size influence energy demand by affecting reaction rates and thermal transfer efficiency [58]. In sectors like cement and ceramics, higher feed moisture increases energy demand for drying and preheating, creating a loop that amplifies fuel consumption unless mitigated by preheating or alternative fuel strategies [30,59]. In the glass sector, both the quality and proportion of cullet affect furnace efficiency by lowering the energy required for melting [62]. Moreover, in both the glass and steel processes, finer particle sizes reduce melting or sintering temperatures [60,61], while in cement, it allows a more efficient chemical reaction [30], forming a balancing loop that enhances energy efficiency when process conditions are optimised. Significant heat losses remain across all high-temperature operations, indicating waste heat recovery as a shared strategy for breaking reinforcing loops [63–66].

The second pathway concerns equipment performance and operational practices. Poor thermal insulation or degraded refractory lining in kilns, furnaces, and firing ovens increases heat loss, requiring additional fuel input, thus amplifying energy consumption [67–69]. Effective process control measures, such as optimising kiln revolutions per minute (RPM), fuel air ratios, and blast furnace injection ratios, generate balancing loops that stabilise combustion efficiency and throughput, counteracting unnecessary fuel consumption [36,61,70].

The third relates to environmental conditions. Ambient air temperature significantly affects energy efficiency across all four sectors. Higher temperatures reduce heat losses by lowering the temperature gradient between processes and their surroundings, while colder conditions accelerate thermal dissipation, increasing fuel consumption [71]. This effect is most pronounced in high-surface-area equipment, where insulation performance is key to minimising losses [72]. Additionally, humidity and air density influence combustion efficiency by altering air-to-fuel ratios, affecting heat transfer and process stability [73].

These findings reveal shared dependencies across sectors, particularly the influence of raw material properties, insulation quality and process control on thermal energy use. While each industry presents unique challenges, common opportunities for intervention emerge. Addressing factors such as feed moisture, refractory degradation and combustion stability can break reinforcing energy loops and enhance efficiency. These insights support cross-sectoral strategies focused on improved process integration, waste heat recovery, and advanced control systems to reduce energy intensity and emissions.





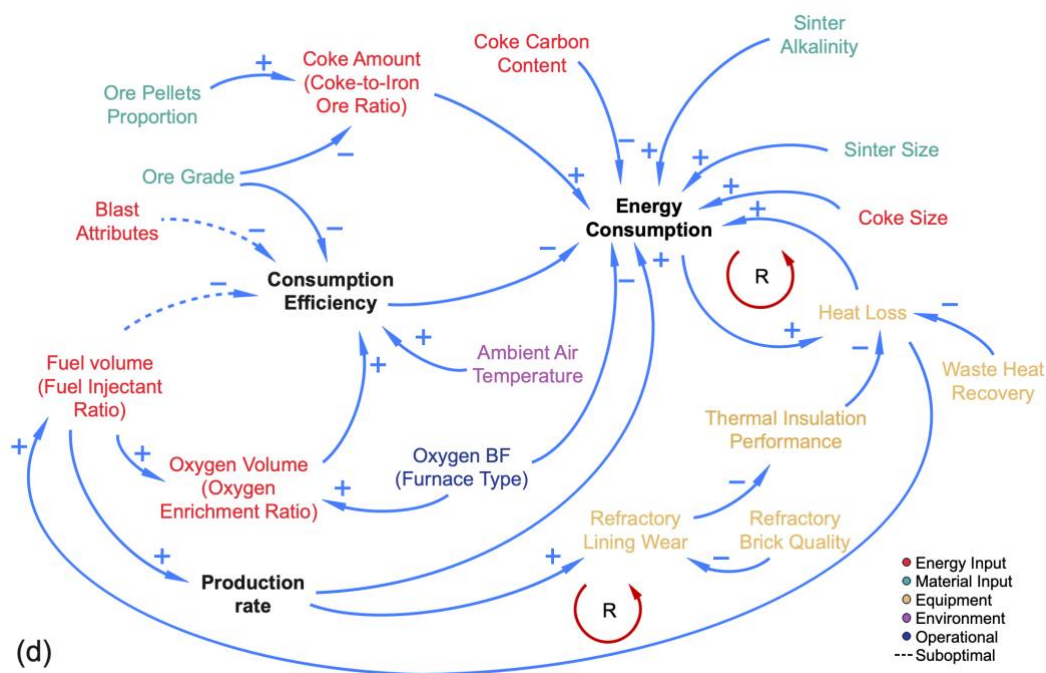


**Figure 27 Causal loop diagrams (CLD) showing interdependencies between influencing factors for a) cement clinkerisation, b) glass melting, c) ceramics firing and d) ironmaking**

#### 4.2.4.3 Energy Thresholds

Energy consumption thresholds provide a comparative procedure for evaluating the potential for energy efficiency improvements within industrial processes. By analysing the gap between current industrial practices, BATs, R&D potential, and theoretical minimums, this section identifies opportunities for energy savings across cement, ceramics, glass, and steel manufacturing.

The energy thresholds for these sectors are presented in Figure 28, where (a) cement, (b) glass, (c) ceramic and (d) steel illustrate the respective energy consumption benchmarks. The percentages reported alongside each threshold comparison represent the relative reduction in energy consumption achievable at each stage. These thresholds highlight the varying degrees of efficiency achieved under different technological scenarios, offering insight into the extent of possible energy reductions through process optimisation and technology adoption.

Across all four sectors, a significant gap remains between current industrial practices and BATs, highlighting the slow uptake of proven energy-saving

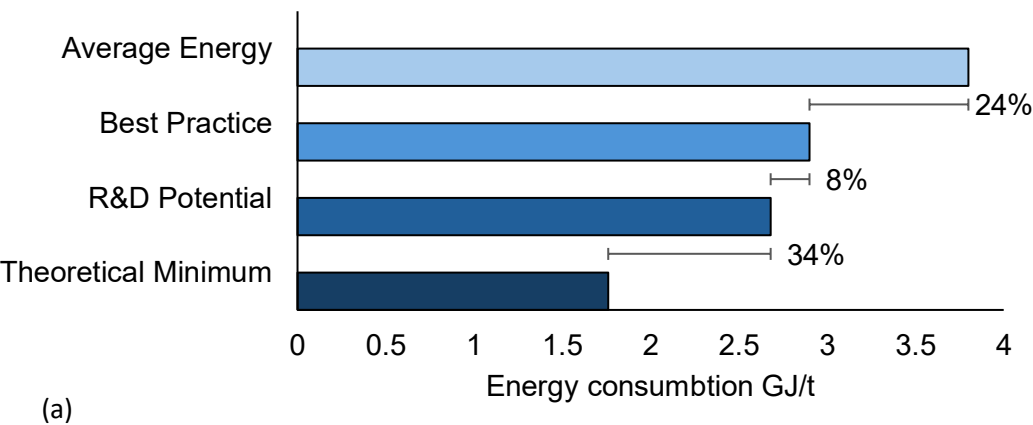
measures. For example, the cement industry exhibits a 24% gap, primarily due to its continued reliance on energy-intensive clinkerisation. Similarly, the glass sector shows a 25% disparity, reflecting persistent challenges in reducing the energy demand of high-temperature melting processes [45,82]. In contrast, ceramics show a smaller gap of 17%, indicating some success in optimising kiln operations, and steel has the lowest at 8%, suggesting comparatively stronger adoption of BATs. Nonetheless, inefficiencies persist across all sectors, particularly in areas such as heat recovery, combustion control, and fuel mix optimisation [76,83].

Looking beyond current practices, some sectors demonstrate greater potential for improvement. Ceramic firing and ironmaking stand out with the largest gains between BAT and R&D potential, each offering an additional 17% and 16% in possible energy savings, respectively. These improvements are linked to developments such as enhanced cooling gas recovery in ceramics [76] and advanced injection techniques in ironmaking [84]. Conversely, cement clinkerisation and glass melting show more limited potential, with only an 8% difference between BAT and R&D levels. These lower margins reflect fundamental constraints within the processes themselves. For instance, cement is limited by the unavoidable calcination step, while glass requires high liquefaction temperatures that restrict the effectiveness of current innovations. Electrified kilns and similar technologies remain promising but are not yet commercially viable [85].

When comparing R&D potential to theoretical minimums, further insights emerge. Ceramic firing again leads with the largest gap of 80% to its theoretical minimum, suggesting major inefficiencies still exist. This can be attributed to ceramics' relatively lower sintering temperatures and simpler reaction chemistry [86]. Ironmaking shows a 19% gap, where reliance on coke-based reduction remains a significant constraint [87]. In comparison, cement and glass retain 34% and 38% gaps, respectively, between their R&D potential and theoretical minimums. These high values highlight the physical and chemical limits of their core high-temperature processes. In cement, the decomposition of limestone drives energy

demand [88], while in glass, the melting characteristics of input materials set an energy floor [89].

Despite sector-specific characteristics, high thermal energy demand, elevated process temperatures, and persistent system losses remain common challenges across all four sectors. These fundamental barriers limit the scope for drastic improvements, even as BATs continue to offer practical near-term opportunities. However, implementation is often constrained by high capital costs, limited demonstrations and operational trade-offs [81–83]. Given the variation in energy thresholds across sectors, strategies must be tailored to each industry's context while also recognising shared pathways. Incremental improvements through process optimisation and material refinement are widely applicable, but deeper efficiency gains will require integrating alternative energy sources, novel material processing methods and more advanced system control. Ultimately, the most transformative impact will come from cross-sectoral learning and technological synergies. Heat recovery techniques developed in ceramics and glass, for instance, could inform improvements in cement kilns, while hydrogen-based methods in steelmaking may hold promise for other high-temperature processes. Leveraging such shared innovations is critical to accelerating industrial energy transitions without compromising productivity or economic resilience [84].



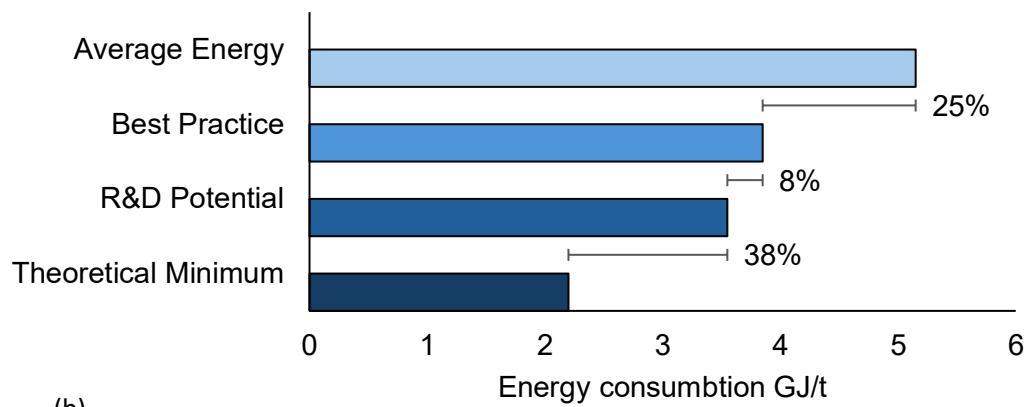
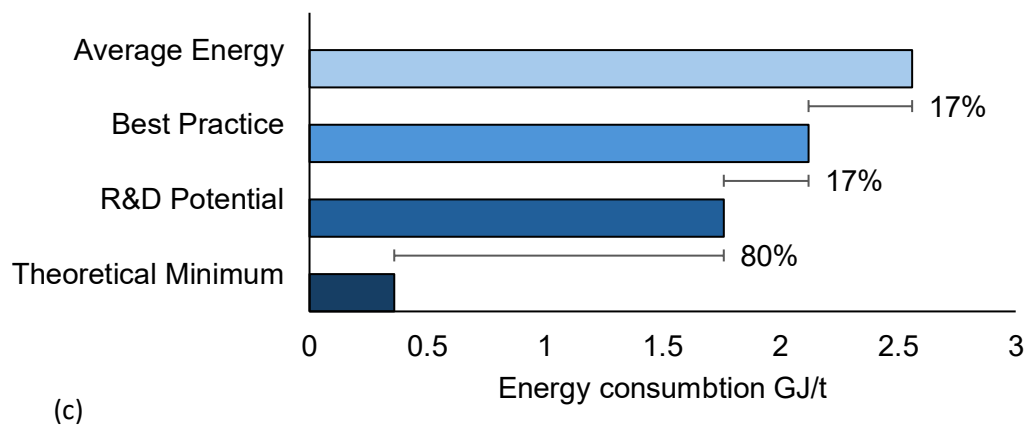
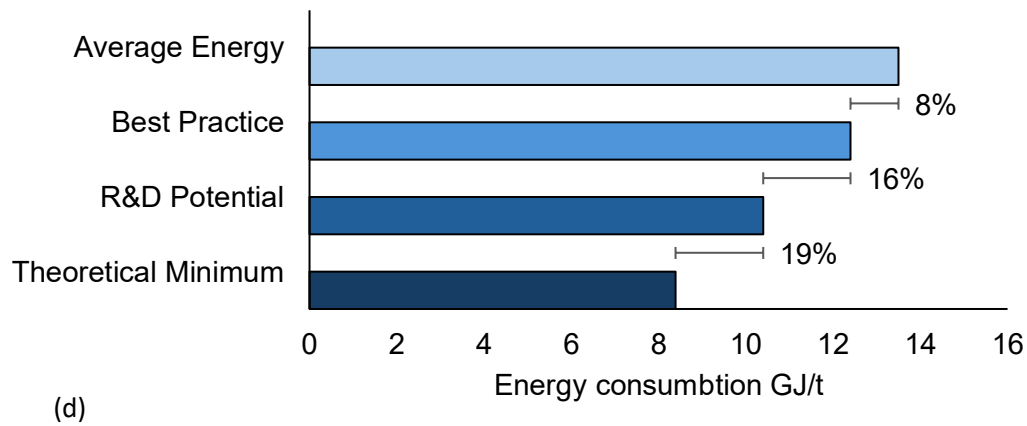


**Figure 28 Energy consumption thresholds for a) cement clinkerisation, b) glass melting, c) ceramics firing and d) ironmaking**

#### 4.2.5 Conclusion

The study provided a comprehensive assessment of energy consumption in the most energy-intensive processes across the cement, ceramics, glass, and steel

industries. By integrating systems-based analysis with benchmarking against best available technologies and theoretical minimums, the work moves beyond general efficiency recommendations to reveal where specific gaps persist, and which intervention points offer the greatest impact. The cross-sectoral perspective underscores the need for both tailored solutions and shared learning, as industries face common obstacles in advancing their energy utilisation and efficiency.

#### **4.2.5.1 Implications for Industry and Academia**

The study offers practical insights for both industrial stakeholders and academic researchers, particularly as the manufacturing sector navigates the dual challenge of improving energy efficiency while transitioning toward low-carbon production. By framing current performance gaps and technological advancements, the analysis informs not only operational strategies but also research directions and policy considerations.

From a research standpoint, this analysis offers a structured procedure for evaluating industrial energy efficiency, highlighting areas where measures are well-established and where gaps persist. It provides a foundation for future research on underexplored aspects of energy optimisation, particularly in refining factor interactions and assessing emerging technologies. However, these opportunities must be viewed within the context of a shifting industrial landscape. Increasingly, technological developments and policy frameworks are prioritising decarbonisation over energy efficiency [85,86]. While traditional strategies focused on minimising energy intensity, many emerging solutions, such as hydrogen-based steelmaking [87], alternative cement binders [88,89] and electrified furnaces [90], are primarily designed to reduce CO<sub>2</sub> emissions and not necessarily to minimise energy consumption. This shift reflects broader climate targets, sustainability commitments, and regulatory pressures favouring carbon neutrality [91].

While this transition is essential for long-term environmental goals, it also presents important trade-offs. Many decarbonisation technologies require higher energy inputs, particularly when replacing fossil fuel-based processes with

alternative reduction agents (e.g., hydrogen or biofuels) or integrating carbon capture and storage (CCS) [92,93]. These changes often require major infrastructure investments, introduce operational complexity, and may reduce short-term competitiveness, particularly in regions with limited access to low-carbon energy. This could exacerbate regional disparities in industrial performance and market resilience. As the sector moves forward, aligning energy efficiency with decarbonisation will be critical. A narrow focus on emissions reduction, without addressing underlying inefficiencies, may limit the environmental and economic gains of the transition. Policymakers, researchers, and industry leaders must therefore work toward integrated strategies that simultaneously reduce carbon emissions, optimise energy use, and support competitive, low-carbon manufacturing systems.

#### **4.2.5.2 Limitations and Future Research**

Several limitations must be acknowledged. External economic and policy factors, such as fuel prices and carbon taxation, were not explicitly considered, despite their potential impact on technology adoption. For instance, fuel costs can impact decisions regarding kiln type or furnace operation, but such economic factors were assumed to be relatively fixed within an established facility. The analysis also assumes process-wide applicability, without accounting for facility-specific constraints like plant layout and equipment condition. Furthermore, while causal relationships between factors were identified, the extent of their interdependencies was not quantitatively modelled. Future research should aim to validate these findings through industry-specific case studies in order to identify possible trade-offs between measures, such as the impact of fuel reduction on combustion stability, which require further investigation. Despite these limitations, this study provides a robust foundation for optimising industrial energy efficiency and guiding future research.

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## **4.3 Benchmarking of Energy Consumption and CO<sub>2</sub> Emissions in Cement Production – A Case Study <sup>5</sup>**

### **4.3.1 Introduction**

Foundation industries including cement, metals, glass, chemicals, paper and ceramics serve as crucial industries, generating wealth and significantly representing a nation's economy and overall strength. These industries provide £52 billion to the UK economy by producing 28 Mt of materials annually [1]. However, while meeting human demands through the production of goods and services, the foundation industries consume substantial amounts of limited energy and materials, often with low energy efficiency and resource conversion rates. This inefficiency leads to significant waste and severe environmental damage [2]. The foundation industries are responsible for around 10% of total CO<sub>2</sub> emissions [3]. Significant energy consumption and emissions growth have led to severe environmental pollution. The 2017 energy efficiency survey report indicates that the global demand for fossil energy continues to rise, resulting in a general increase of over 30% in global energy consumption [4]. Notably, the industrial sector is a major contributor to this escalating energy demand, accounting for more than 53% of the nation's total energy consumption [5]. In this context, it is critical for foundation industries to improve their environmental sustainability and reduce their resource consumption. Benchmarking is a powerful tool that helps industries identify and prioritise opportunities to improve energy efficiency and environmental sustainability [6– 8]. This tool has been well-developed for more than 40 years, after first being used by Xerox Corporation in the early 1980s. Xerox's approach involved studying and learning from various industries, not just its direct competitors, in order to identify best practices and innovative strategies that could be applied to their operations [9].

The cement industry ranks as the third-largest consumer of industrial energy worldwide, responsible for approximately 7% of global industrial energy

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<sup>5</sup> S. Sarfraz, Z. Sherif, M. Jolly, and K. Salonitis, "Benchmarking of energy consumption and CO<sub>2</sub> emissions in cement production: A case study," in TMS 2024, pp. 35–46.

consumption and ~7% of global CO<sub>2</sub> emissions, faces particular challenges in achieving sustainability due to its inherent energy- and emissions-intensive production processes [10, 11]. Although the cement industry recognises the need to reduce its environmental impacts, benchmarking initiatives remain limited [12]. Global studies reveal wide variability in energy efficiency and carbon emissions between different cement plants, suggesting major potential for improvement through systematic benchmarking [12]. However, comprehensive data is lacking, as cement producers are often reluctant to share detailed operational insights. This study focuses on benchmarking the energy usage and carbon emissions of a UK cement plant to pinpoint opportunities for enhancing efficiency and reducing environmental impacts. A tailored benchmarking methodology that incorporates BAT analysis has been developed to evaluate the cement plant's thermal energy intensity, electrical energy intensity, waste heat recovery, CO<sub>2</sub> intensity and capacity utilisation. Metrics are compared against industry best practices to highlight potential areas for improvement. The primary objective of this study is to enhance the sustainability of energy and emission intensive manufacturing processes, with a strong focus on environmental considerations and resource efficiency. Therefore, this study aims to achieve this by introducing a benchmarking approach, which offers a systematic method for evaluating and enhancing the sustainability of manufacturing systems. Ultimately, this endeavour is expected to foster the growth and advancement of the manufacturing industry while promoting environmentally friendly practices and resource conservation.

### **4.3.2 Benchmarking Approach Development**

This section outlines the steps involved in the benchmarking approach development process and provides the rationale behind each step.

#### **4.3.2.1 Understanding the Manufacturing Operations of Foundation Industries**

A generic process model has been developed to elucidate the key elements involved in manufacturing operations across various foundational industries (Figure 29). This model illustrates the typical inputs and outputs that are inherent

to production processes. Inputs encompass raw materials, electricity, and fuel, which provide the physical components, energy, and power needed to enable manufacturing activities. Outputs include the desired final manufactured products, as well as waste streams and carbon dioxide emissions, which tend to be unavoidable byproducts of industrial production. A salient feature of the model is its illustration of process heat recovery as a key component. Many manufacturing processes intrinsically generate significant waste heat, which represents a loss of energy efficiency if not harnessed. Thus, incorporating heat capture and reuse into process designs can dramatically improve the energy efficiency and environmental profile of manufacturing. Additionally, the model highlights machine capacity utilization as a vital parameter in optimising industrial production. Running machines at maximum capacity boosts productivity and diminishes per-unit costs. However, energy, materials, and labour must be balanced to avoid inefficiencies associated with over-capacity.

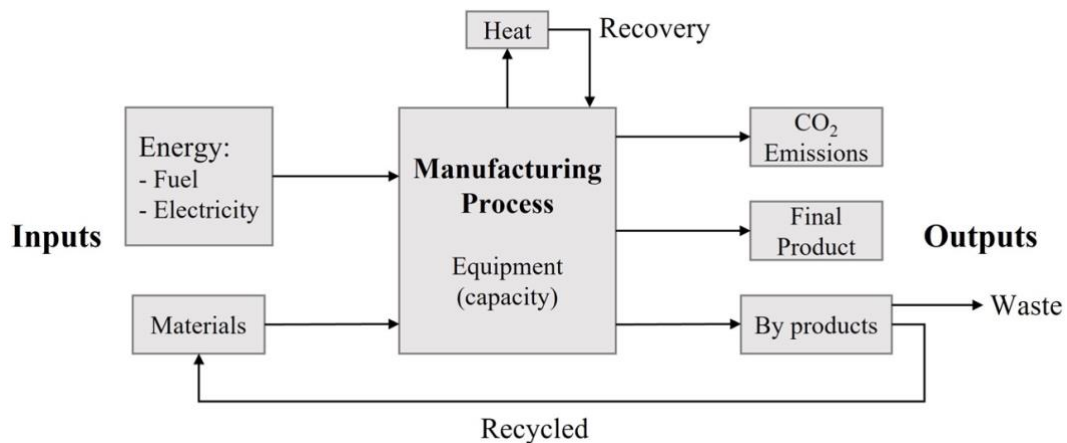


**Figure 29 Generic manufacturing process model of inputs-outputs**

#### **4.3.2.2 Identification of Key Process Metrics**

Both intensity and performance-based metrics have been utilised in this work to evaluate manufacturing efficiency from complementary perspectives. As noted by Jaller and Matthews [13], intensity-based measures that quantify emissions per unit output offer valuable insight into efficiencies, as declining emissions per product indicate improved environmental performance over time. Though intensity metrics do not directly correlate with overall emission reductions, they

enable critical trend analyses. Furthermore, performance metrics that gauge the achievement of economic and regulatory targets are essential, as highlighted by Ogunsiji and Ladanu [14]. In a manufacturing context, performance indicators provide insights into operational performance while highlighting performance gaps and continuous improvement opportunities. Thus, this study employs intensity metrics for their utility in tracking efficiency gains, alongside performance metrics to assess broader goal attainment. This dual intensity and performance-based approach thereby enables a multidimensional assessment of manufacturing efficiency. The chosen metrics along with description and units are provided in Table 14.

**Table 14 Vital sign metrics for manufacturing sustainability**

| Metric                      | Description                                                      | Formula                                                                   | Unit                |
|-----------------------------|------------------------------------------------------------------|---------------------------------------------------------------------------|---------------------|
| Thermal energy intensity    | The amount of thermal energy used to produce a unit of output    | $\frac{\text{(Thermal energy consumed)}}{\text{(Unit mass Produced)}}$    | kWh/t               |
| Electrical energy intensity | The amount of electrical energy used to produce a unit of output | $\frac{\text{(Electrical energy consumed)}}{\text{(Unit mass Produced)}}$ | kWh/t               |
| Energy recovered (heat)     | The amount of energy recovered or reused from the process        | $\frac{\text{(Recovered energy)}}{\text{(Total energy waste)}}$           | %                   |
| CO <sub>2</sub> intensity   | Total direct emissions per unit mass produced                    | $\frac{\text{(CO}_2\text{ emissions)}}{\text{(Unit mass Produced)}}$      | tCO <sub>2</sub> /t |
| Capacity utilisation        | The extent to which production capacity is being used            | $\frac{\text{(Actual output rate)}}{\text{(Max possible output rate)}}$   | %                   |

#### 4.3.2.3 Data collection points

##### Industry data collection

Based on the selected metrics, a data template was developed to facilitate the benchmarking process, as shown in Table 15. This will capture and organise multiple entries, such as product type, equipment used, process conditions, process specification, and measurement methods used which is an important part of data collection.

**Table 15 Data collection template**

| Process Data Form |                             |      |                    |               |
|-------------------|-----------------------------|------|--------------------|---------------|
|                   | Process                     |      |                    |               |
|                   | Product type                |      |                    |               |
|                   | Equipment used              |      |                    |               |
|                   | Process conditions          |      |                    |               |
|                   | Process Specification       |      |                    |               |
|                   | Metrics                     | Unit | Measurement Method | Current Value |
| 1                 | Thermal energy intensity    |      |                    |               |
| 2                 | Electrical energy intensity |      |                    |               |
| 3                 | Energy recovered            |      |                    |               |
| 4                 | Capacity utilisation        |      |                    |               |
| 5                 | CO <sub>2</sub> intensity   |      |                    |               |

The measurement method used to collect data affects the accuracy of the data. For example, collecting data using sensors on the machine or equipment (such as an energy meter) can provide more accurate data than using bill data or production output data. Additionally, it pinpoints the extent of the data presented, whether it directly results from the process or encompasses other aspects beyond the process (such as indirect emissions or auxiliary energy consumption). The current value represents the value provided by the manufacturer which was compared with the global average and best practice values.

### **Literature data collection**

This outlines the procedure adopted to collect essential data from the literature, comprising global average and best practice values, as well as best available techniques (BATs) and their associated impacts and costs. The gathered information is instrumental in assessing company performance, comparing it with industry standards, and exploring potential avenues for efficiency improvement. This establishes the basis for evaluating manufacturing processes and the potential adoption of BATs.

## **Global and best practice values**

The procedure employed in this study follows a comprehensive approach to gather data concerning global average values, as well as best practice benchmarks, relevant to the various identified metrics. A literature review was conducted to collect relevant information from articles, industry reports, and government publications. The primary aim of this data collection was to establish a solid foundation for benchmarking the manufacturing processes under investigation. By analysing these averages and best practice standards, this study intends to assess company performance and compare operational data against industry norms, facilitating the identification of areas for potential improvement and efficiency enhancement.

## **BATs, their impact and associated cost of implementation**

Within the approach, a thorough exploration of BATs for the manufacturing processes under scrutiny was undertaken. A comprehensive examination of BATs, including their associated impacts, as well as the estimated costs of implementation, was conducted. This analysis drew upon data derived from various studies, governmental bodies, and environmental agencies. The main objective of this analysis was to provide a comprehensive understanding of the potential benefits and economic implications associated with the adoption of BATs. By evaluating the feasibility and cost-effectiveness of BAT implementation, this study aims to assist companies in making informed decisions concerning process improvements, while also quantifying the resulting savings in energy consumption.

### **4.3.3 Developed Benchmarking Approach**

The benchmarking approach adopted in this study (Figure 30) is structured around three key pillars. The first pillar involves an extensive literature review, which encompasses the collection of data on best practices, global averages, and BATs along with their associated environmental and cost considerations. The second pillar centres on the acquisition of industry-specific data, including production, processing, and equipment-related information within the

manufacturing processes under examination. The final pillar revolves around data analysis, which includes the comparative assessment of industry data against benchmarks, an evaluation of the potential impact of best practices and BATs, and the estimation of cost savings. This holistic approach equips the study with the necessary insights to evaluate manufacturing processes objectively, identify areas for enhancement, and make informed decisions concerning efficiency improvements and sustainability.

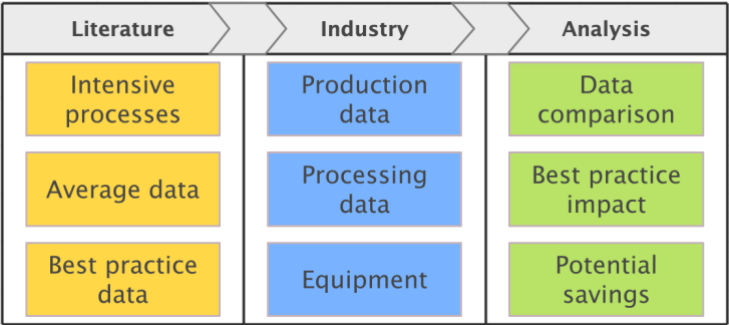


**Figure 30 Benchmarking approach overview**

### 4.3.4 Case study results and discussion

Utilising the developed benchmarking approach, a case study was conducted with a prominent cement manufacturer based in the UK having a plant capacity of 2850t/day. Notably, the cement manufacturing industry, one of the major foundation industries, stands as a significant consumer, demanding nearly 15% of the total industrial energy use due to its energy-intensive processes [15]. The case study reveals significant relevance for advancing sustainable practices within this vital sector.

#### 4.3.4.1 Industry vs. literature metrics data

A detailed comparison was conducted between data sourced from the industry, employing the developed data collection template, and data obtained from the literature. The dataset encompasses three pivotal processes: raw meal grinding, clinkerisation, and finish grinding, collectively constituting 20%, 25%, and 40% of the total energy demand in cement production, respectively [16]. Specifically, the clinkerisation stage is scrutinized for thermal energy intensity, heat energy recovery, CO2 intensity, and capacity metrics. In contrast, electrical energy

intensity is analysed across all stages. The data are presented in Figure 31. This evaluation revealed that the performance of the plant in question surpasses global average values in all aspects for all stages. However, there is still room for improvement as their values fall short of best practice benchmarks both globally and in Europe.

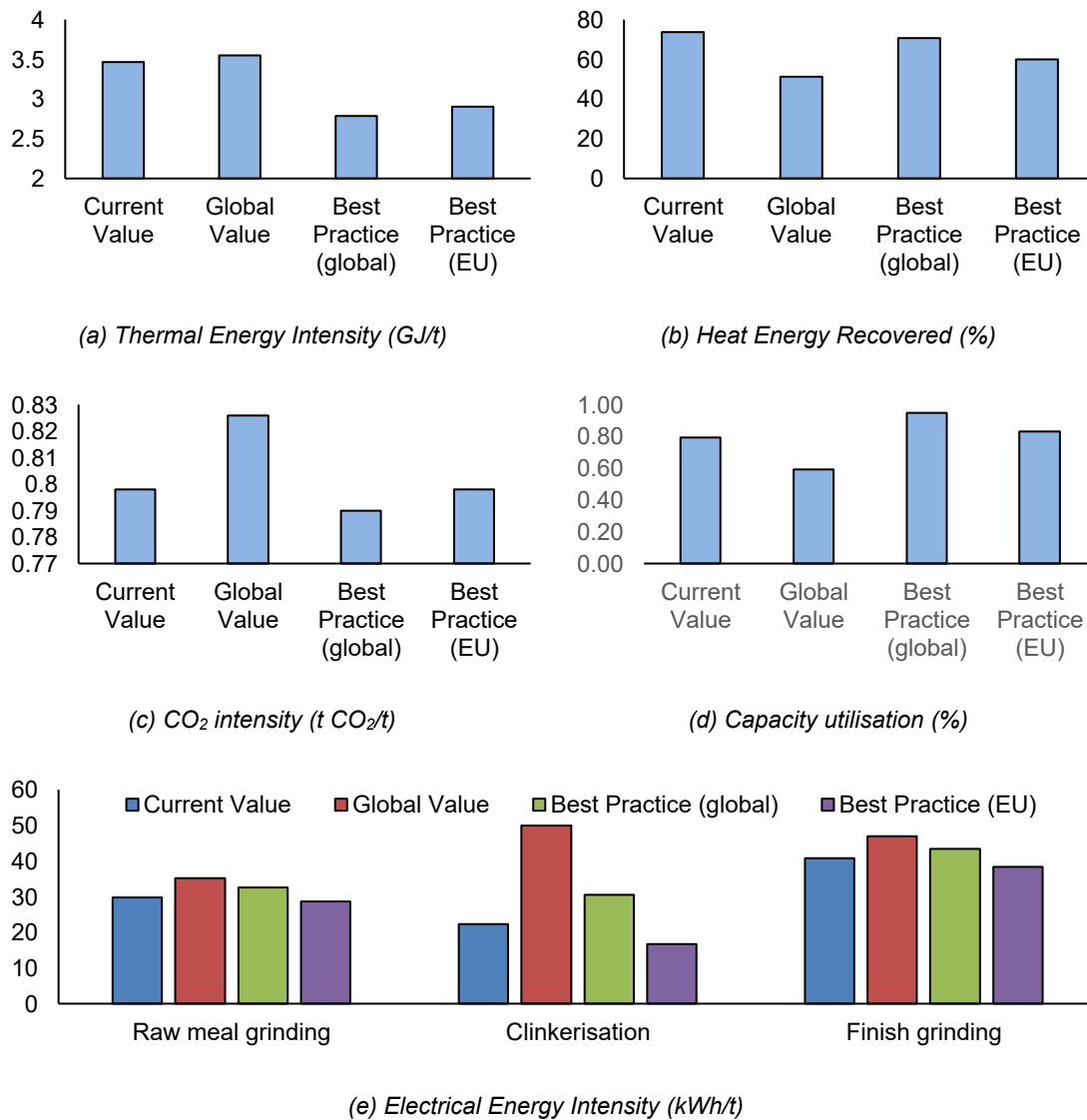


**Figure 31 Industry VS literature data visualisation. (a) to (d) represents the Clinkerisation stage only while (e) shows all three stages. Data from [16–26]**

#### 4.3.4.2 BATs Identification and Analysis

The subsequent step entailed the acquirement of BATs relevant to cement manufacturing. Tackling energy consumption was prioritised and for this reason,

BATs related to energy consumption were examined. This includes detailed data on their associated electrical and thermal energy savings, as well as implementation costs, sourced from literature. The dataset comprises BATs tailored to the three production stages, in addition to generic techniques with broader applicability across the entire cement plant (Table 16). This compilation phase establishes the groundwork for the evaluation of potential improvements within the studied industry.

**Table 16 Cement BAT, their energy impact and associated cost [27–31]**

|    | BAT applicable to the cement sector<br>(Energy)                                              | Savings            |                   | Implementation<br>Cost (M€) |
|----|----------------------------------------------------------------------------------------------|--------------------|-------------------|-----------------------------|
|    |                                                                                              | Electric<br>(MJ/t) | Thermal<br>(MJ/t) |                             |
| 1  | Replacing a ball mill with a vertical roller mill in raw material grinding                   | 39.6               | 0                 | 29.9                        |
| 2  | Use of gravity-type homogenising silo for raw material blending                              | 10                 | 0                 | 6                           |
| 3  | Changing from long kilns to kilns with cyclone preheaters and pre-calciner                   | 19                 | 0                 | 85                          |
| 4  | Organic Rankine Cycle (ORC) for power generation through waste energy recovery               | 18                 | 900               | 22.5                        |
| 5  | Changing from rotary or satellite coolers to modern grate coolers                            | 57.6               | 0                 | 17.5                        |
| 6  | Using 5 or 6 stage cyclone preheater                                                         | -12.6              | 200               | 6.5                         |
| 7  | Replacing ball mills with vertical roller mills in cement grinding                           | 90                 | 0                 | 25                          |
| 8  | Using high efficiency separator for cement grinding                                          | 93                 | 0                 | 1.5                         |
| 9  | Using variable speed drives for all fans                                                     | 14                 | 0                 | 2.6                         |
| 10 | Introduction of process control optimisation (Advanced plant control systems)                | 8.5                | 150               | 0.65                        |
| 11 | Replace low efficiency motors with premium and super premium efficiency motors (IE3 and IE4) | 16                 | 0                 | 0.16                        |

#### **4.3.4.3 Industry BAT adoption and impact**

Following the identification and assessment of the applicable BATs employed by the company, a commendable adoption of the majority of recognised techniques was revealed. Nevertheless, two notable exceptions emerged. The first pertains to the untapped potential of harnessing power through waste energy recovery at the clinkerisation stage, a prospect offered by the Organic Rankine Cycle (ORC).

The second involves the integration of vertical roller mills (VRM) for cement grinding, showcasing opportunities for further refinement in the company's manufacturing processes.

The potential energy intensity values are computed based on the savings conceivable by adopting the lacking BATs and compared to the best practice values. In the case of clinker production, the potential electrical intensity could be reduced by 22%, reaching the best practice value (Figure 32(a)) while the thermal energy could be reduced by 26%, outdoing the best practice data (Figure 32(b)). Furthermore, utilising VRM for cement grinding could potentially reduce the electrical energy consumption by 61%, surpassing best practice energy use values, as shown in Figure 32 (a).

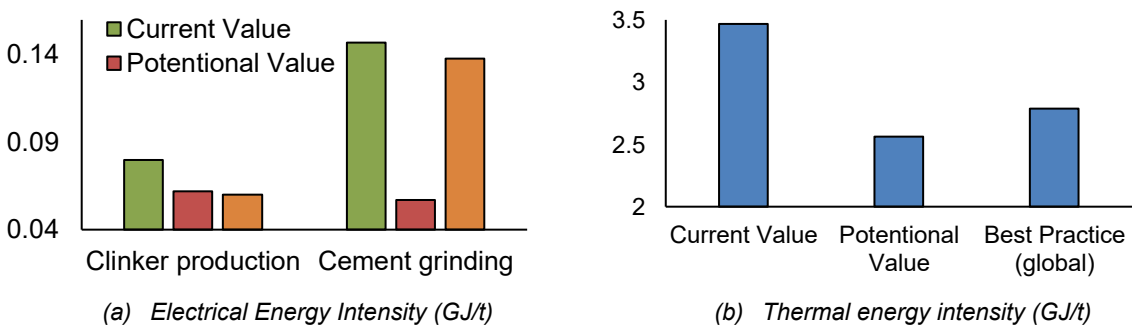


**Figure 32 Current and potential energy values comparison for a) Electrical energy intensity and b) Thermal energy intensity**

The potential total energy savings of each stage have been compared with the implementation cost of the identified BATs. As seen from Figure 33, it is evident that the BAT for cement grinding not only incurs lower implementation costs but also yields greater energy savings.

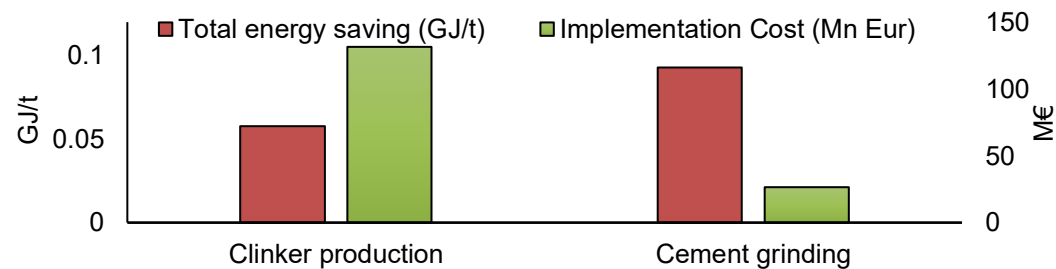


**Figure 33 Energy saving (GJ/t) VS Cost (M€)**

#### **4.3.5 Conclusion**

This study demonstrates the value of benchmarking as a tool for assessing and improving the energy efficiency and carbon footprint of energy-intensive manufacturing processes, using a UK cement plant as a case study. The benchmarking analysis quantified the plant's energy intensity and CO<sub>2</sub> emissions per tonne of cement produced across key process stages including raw material grinding, clinker production, and cement grinding. Performance gaps were revealed relative to current global averages and best practices.

The study also compiled relevant BATs for the cement sector, revealing additional prospects to integrate vertical roller mills for cement grinding and use Organic Rankine Cycle to increase waste heat recovery. Adopting these BATs could reduce the cement grinding electrical energy intensity by 61% and clinkerisation thermal intensity by 26%, surpassing global benchmarks. A preliminary economic analysis further showed cement grinding improvements offer substantial energy savings at relatively low implementation costs.

Overall, this research demonstrates the usefulness of a benchmarking procedure that incorporates BATs for cement manufacturers to identify performance gaps, best practices and efficiency opportunities. Although limited to a single cement plant, the standardised methodology could be replicated across multiple sites to support step-change improvements industry wide. The approach could also be adapted to enhance sustainability in other foundation industry sectors. The study acknowledges certain limitations in its methodology. While BATs affecting energy consumption are thoroughly examined, their impact on emissions is not included in this analysis. Additionally, while energy savings are compared to initial implementation costs, long-term cost-effectiveness is a factor that warrants further consideration. Moreover, the study takes into account the cost of implementation in a generalised sense, without delving into the specific costs that may be influenced by plant layout and other site-specific factors. These limitations serve as areas for potential refinement and consideration in future analyses.

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#### **4.4 Contribution of Papers to Thesis Objectives**

The two papers presented in this chapter contribute directly to Objective 3 by implementing benchmarking techniques to evaluate process-level performance, identify inefficiencies and inform energy and emissions reduction strategies in manufacturing.

The first study provides a cross-sectoral view of energy use in the foundation industries. Through energy mapping, causal loop diagrams and benchmarking against BATs and theoretical minimums, it identifies process inefficiencies and interdependencies that limit improvement. This work contributes not only by highlighting energy-related gaps but also by illustrating how influencing factors can be structured for performance evaluation and the identification of improvement plans.

The second study complements this with a case study. It introduces a replicable benchmarking approach that aligns performance indicators with BAT adoption. The study also considers implementation costs, adding a layer of practical relevance for industry stakeholders.

Together, the papers:

- Identify key energy efficiency gaps while highlighting the need to align decarbonisation efforts with operational optimisation.
- Demonstrate how structured benchmarking and BAT adoption analysis can reveal actionable improvements at the process level.

These contributions strengthen the thesis's overarching aim of delivering scalable, process-focused sustainability tools for manufacturing systems, grounded in both strategic analysis and operational feasibility.

## **5 Greening Foundation Industries: Shared Processes and Sustainable Pathways <sup>6</sup>**

### **5.1 Paper Linkage to Research Aim and Objectives**

This chapter addresses Objective 4, which focuses on identifying cross-sectoral improvement opportunities through shared process analysis. The rationale for this study stems from the recognition that Foundation Industries, while diverse in their products and technologies, share several processes that could be targeted for coordinated sustainability action. However, there has been limited effort to methodically explore these commonalities to support joint improvements or knowledge transfer.

To address this gap, the paper presents a structured analysis of shared manufacturing processes across six industries. It integrates process mapping, classification and intensity analysis which enabled the identification of common processes across sectors. This cross-sectoral perspective on resource use and environmental impact supports the thesis goal of developing transferable sustainability strategies at the process level. It also helps prioritise improvement efforts based on process prevalence and potential for impact.

This chapter extends the thesis narrative beyond sector-specific assessments to consider the broader industrial ecosystem, where shared challenges may be addressed through shared solutions.

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<sup>6</sup> Z. Sherif, S. Sarfraz, M. Jolly, and K. Salonitis, "Greening foundation industries: Shared processes and sustainable pathways," Sustainability, 2023.

## 5.2 Introduction

Foundation industries (FIs), including metals, ceramics, cement, paper, chemicals, and glass, play a vital role in supporting industrial economies around the world. They are responsible for 59% of the total energy used by the manufacturing sector of the U.S. [1] and produce 75% of all materials used in the UK [2]. These industries provide essential materials and products that serve as building blocks for various sectors, such as construction, transportation, packaging, and energy generation [3]. However, the manufacturing industry, including FIs, faces significant challenges in terms of sustainability and resource utilisation. The growing concerns about climate change, resource scarcity, and environmental degradation have necessitated a re-evaluation of manufacturing practices to promote sustainability.

Manufacturing processes in FIs are known to consume substantial resources and have a considerable impact on the environment [4]. For instance, cement manufacturing accounts for 8% of global CO<sub>2</sub> emissions [5] and 7% of the global industrial energy demand [6]. This poses significant challenges to the industries' sustainability and long-term viability [7]. Therefore, it is crucial to assess and enhance the energy performance of these industries to align with the broader goals of sustainable development. The lack of comprehensive assessment and analysis of the most important manufacturing processes in FIs hinders progress towards sustainability [8, 9]. Furthermore, while these industries share many common processes, there are little or no studies signifying the commonality of these processes in terms of technicality and operations. Without a clear understanding of the most critical processes driving energy consumption, it is challenging to identify and prioritise areas for improvement and implement sustainable practices effectively.

Existing literature proposes various classification mechanisms for manufacturing processes which are normally for a particular purpose, such as process selection [10,11]. These are often specific to individual sectors, such as metal machining and joining [12] and ceramics restorative materials [13] or a specific type of production, such as additive manufacturing [14]. Conversely, classifications are

too generic to be useful, for example, by classifying according to the nature of the process in terms of chemical or physical change [15]. A comprehensive universal classification system applicable across all sectors is lacking.

This research aims to address these critical gaps by identifying and evaluating the most significant processes common within FIs. Through a methodical examination of commonality within these industries and along with their energy and emissions implications, this research establishes the groundwork for informed decision-making and targeted interventions. Stakeholders can prioritise actions and allocate resources for the greatest sustainability improvements considering significant processes. Furthermore, this research opens avenues for collaboration and knowledge sharing among different sectors, fostering a cross-industry dialogue and collective effort towards sustainable manufacturing practices.

Since the manufacturing industry is a significant contributor to resource consumption and environmental degradation, sustainable manufacturing practices can lead to increased operational efficiency, reduced waste generation, and lower resource consumption, thereby improving the economic viability and competitiveness of manufacturers [16]. Moreover, by adopting sustainable practices, the manufacturing industry can contribute to several Sustainable Development Goals (SDGs) [17]. SDG 9 emphasises sustainable industrialisation and technological advancements, which aligns with the identification of areas for improvement and adoption of best practices in sustainable infrastructure and manufacturing processes. SDG 12 focuses on responsible consumption and production, and the evaluation of resource utilisation and environmental impact contributes to identifying opportunities for resource efficiency within FIs. Additionally, this research supports SDG 13's aim of combating climate change by assessing environmental implications and identifying opportunities for reducing emissions and energy consumption.

In summary, this research addresses the gap in understanding the significance of common manufacturing processes in FIs. Identifying and evaluating these processes promotes sustainability by informing decision-making, prioritising

actions, and fostering collaboration among sectors. Ultimately, this research intends to enhance the environmental performance of FIs and advance sustainable manufacturing practices for a greener future.

## **5.3 Methodology**

This section outlines the methodology employed in this study to identify common processes as well as analyse their emissions and resource utilisation. The methodology encompasses steps incorporating industry selection, process mapping, commonality evaluation, process analysis, and identification of abatement options. By following this systematic approach, the research aims to provide valuable insights into the common processes, their impact, and the potential for implementing best practices to enhance sustainability and energy utilisation across the FIs.

### **5.3.1 Industry selection**

The selection of industries is a key first step in this research. Each of the sectors under consideration comprises various products, and for each product, there may be different production routes. To manage the extensive number of products and routes within each sector, a filtration process is employed. One product is chosen from each sector to perform this exercise as a proof of concept. This is accomplished by identifying the most widely produced products within each sector and then selecting the most commonly used production route for those products. This approach allows for capturing the processes that are most representative of the industry's overall energy utilisation and environmental emissions while keeping the research focused and feasible. Furthermore, this filtration procedure ensures that the research focuses on processes that have a substantial impact on the overall emissions and energy use.

### **5.3.2 Process mapping**

The subsequent stage is creating process maps, a crucial step in comprehending the distinct stages within the production cycle of the chosen products. This is accomplished by visually delineating the primary production process spanning from raw material preparation to finishing, as illustrated in Figure 34. This

clarification facilitates the assessment of their respective importance, thereby establishing the basis for subsequent analysis and comparison.

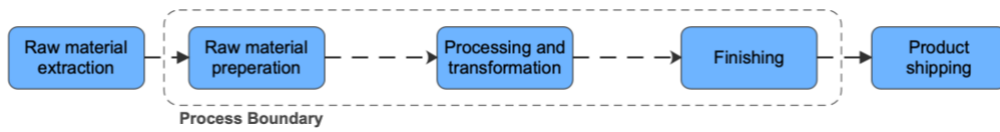


**Figure 34 Process mapping boundary**

### 5.3.3 Commonality matrix

The development of a commonality matrix is essential for identifying and understanding the shared processes across the selected sectors. Dependency Structure Matrix (DSM), a technique utilised to investigate the modularity of products [18], prevalent in the automotive sector, has been adapted to identify commonality across FIs' processes [19]. A template is shown in Table 17. Additionally, by creating a three-tier classification system based on processing principle, outcome, and equipment, a framework is established for comparing processes across sectors (principle = 1, output = 2, and equipment = 3). In more detail, process commonality is firstly assessed in terms of the principle of the underlying concept or method employed in a manufacturing process, representing the fundamental approach or technique deployed. Secondly, it is evaluated on the outcome, desired result or objective achieved through the manufacturing process which represents the end product or the specific goal that the process aims to accomplish. Lastly, the commonality is considered in terms of equipment, which refers to the machinery, tools, and devices used in the manufacturing process [12, 17, 18]. Such information can facilitate knowledge transfer and collaboration among sectors, enabling the exchange of best practices and efficiency measures.

**Table 17 Commonality matrix template**

|          |           |   |           |           |           |           |           |
|----------|-----------|---|-----------|-----------|-----------|-----------|-----------|
| Sector A | Principle | 1 | Process A | Process B | Process C | Process D | Process E |
|          | Outcome   | 2 |           |           |           |           |           |
|          | Equipment | 3 |           |           |           |           |           |
|          | Process A |   |           |           |           |           |           |
|          | Process B |   |           |           |           |           |           |
|          | Process C |   |           |           |           |           |           |
|          | Process D |   |           |           |           |           |           |
|          | Process E |   |           |           |           |           |           |

#### 5.3.4 Process analysis

The process analysis step builds upon the commonality matrix to further examine the identified common processes. Scoring the commonality tiers allows for prioritising the most prevalent and significant processes in terms of their commonality across sectors. This provides insights into the critical areas where collaboration and knowledge sharing can yield the greatest sustainability improvements. Additionally, by listing the top thermal and electrical energy-intensive processes, as well as the top CO<sub>2</sub> emitters, the correlation between intensity and commonality can be explored, identifying potential areas where significant energy efficiencies and emission reductions can be achieved.

#### 5.3.5 Abatement options

The final step involves identifying various abatement options for the common processes identified in the previous steps. This involves looking into best practices and emerging technologies tackling energy and emissions of processes. The aim is to determine whether an option available for a specific process in one industry can be applicable and beneficial for another industry. This approach promotes the adoption of proven and effective practices that have already demonstrated benefits in other sectors.

To sum up, the methodology encompasses a systematic approach to address the research aim. The selection of industries and processes, coupled with process mapping, commonality analysis, process analysis, and identification of abatement options, provides a comprehensive understanding of resource

utilisation and opportunities for improvement within the FIs. The methodology ensures a rigorous and structured approach to generate valuable insights for manufacturers, policymakers, and other stakeholders, facilitating the transition towards sustainable manufacturing practices.

## **5.4 Results**

This section presents and discusses the key findings from the material and route selection process, commonality matrix analysis, and identification of abatement options. It provides valuable insights into production characteristics, energy utilisation, CO<sub>2</sub> emissions and opportunities for sustainable manufacturing practices within the studied sectors.

### **5.4.1 Material selection and process mapping**

The product and route selection process for each sector revealed important insights into the production characteristics and environmental implications within the respective industries. The product selection process was based on global production data or major producing country production volumes, depending on the availability of data. Regarding route selection, the most popular production method is selected for the analysis.

#### **5.4.1.1 Metals**

Steel emerged as the dominant metal in terms of production volume, driven by its versatile applications across industries such as construction and manufacturing. With a global production volume of 1958 million metric tons (Mmt) in 2021 [22,23], steel production exceeded the second-ranked metal, aluminium, by a significant margin (30 times more) as presented in Figure 35 (a). For steel production, the primary route selected was the BF BOF (Blast Furnace - Basic Oxygen Furnace) method. This choice was influenced by the method's widespread use and popularity in the industry, representing 70% of global steel production [30]. However, it is important to note that although the electric arc (EAF) method is known for its environmental friendliness [31], its viability is dependent on the availability of scrap steel.

#### **5.4.1.2 Glass**

Among the various types of glass, container glass emerged as the dominant product in terms of production. As shown in Figure 35 (b), glass containers accounted for approximately 45% of global glass production in 2018 [24], highlighting their significant contribution to the industry. This high production volume can be attributed to the extensive use of glass containers in packaging applications, such as bottles and jars. Regarding the route selection for glass production, the press and blow method was identified as the predominant and commonly used technique [32]. This method involves the formation of glass containers by pressing molten glass into moulds and then using compressed air to blow the glass into the desired container shape [33]. It has gained popularity due to its efficiency and versatility in producing a wide range of container designs and sizes.

#### **5.4.1.3 Chemicals**

Among bulk chemicals, plastics have taken the lead as displayed in Figure 35 (c), with approximately 43% of chemicals produced in the U.S. (2<sup>nd</sup> largest chemical producer) in 2019 being exclusively plastics [25], indicating their pivotal role in various industries such as packaging, construction, and automotive. The remaining 57% of chemical production primarily comprised ammonia, sodium hydroxide, and chlorine, among other products that could be used as constituents for plastic manufacturing. In terms of route selection, the focus was placed on the production of olefins, which serve as fundamental building blocks for plastics. The steam cracking method was identified as the primary process for olefin production, renowned for its vital role and elevated energy intensity within the petrochemical industry due to its highly endothermic nature [34]. Around 98 % of the global production of ethylene is carried out in steam crackers which is the feedstock for polyethylene (PE) plastic, the most commonly produced plastic [35], with the dominant feedstock for worldwide ethylene production being naphtha (55%) [36]. The steam cracking method involves the thermal decomposition of hydrocarbon feedstocks, typically derived from crude oil or natural gas, to yield

olefins like ethylene and propylene, which are extensively used in plastic manufacturing [37].

#### **5.4.1.4 Ceramics**

In the ceramics sector, ceramic tiles were identified as the most energy-consuming product to produce. The tiles industry accounted for nearly 31% of the EU total production value within the ceramics sector signified by the global production of 18 billion m<sup>2</sup> [26,27,29] as presented in Figure 35 (d). This highlights its significant energy demand compared to other ceramics products. Regarding the route selection for ceramic tile production, the pressing method was identified as the primary and prevailing technique employed in the industry. This method involves the use of pressure to shape and form ceramic tiles from clay or other ceramic materials [38].

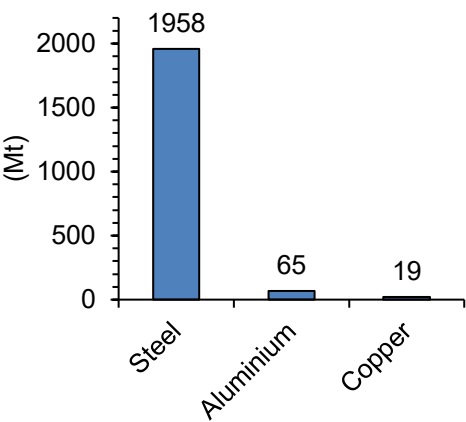
#### **5.4.1.5 Paper**

Packaging paper stood out as the predominant type of paper, accounting for a substantial 63% of global production in 2021 [39], as shown in Figure 35 (e). This significant share can be attributed to the increasing demand for packaging materials, especially in the rapidly expanding e-commerce and consumer goods sectors. In terms of route selection, the widely adopted kraft pulping method was chosen for paper production. This method represents the prevailing industrial trend in global paper manufacturing [40]. The kraft pulping process involves the chemical breakdown of wood fibres using a combination of heat, chemicals, and mechanical action. This technique is known for its efficiency in extracting cellulose fibres and removing impurities, resulting in high-quality pulp suitable for producing various types of paper, including packaging paper [40].

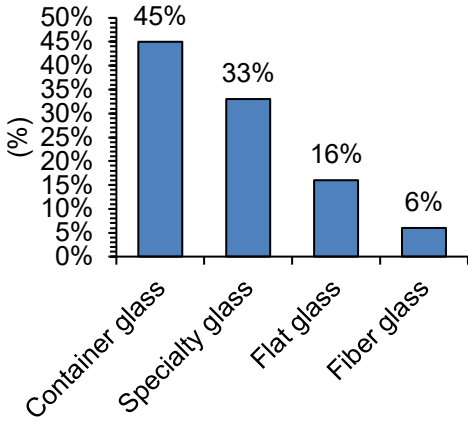
#### **5.4.1.6 Cement**

In terms of product selection, cement products are distinguished by the ratio of clinker to other additives or aggregates in their formulation, which can range from 100% to 20%. Globally, clinker production accounted for a substantial 90% of the total cement produced in 2021 [28] as portrayed in Figure 35 (f). This high proportion of clinker highlights the industry's significant environmental impact, as

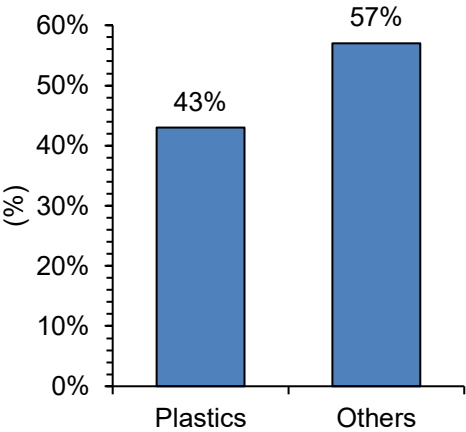
clinker production is known to be energy-intensive and releases considerable carbon dioxide emissions [41]. Regarding route selection, the dry method was identified as the primary production route for cement. The dry method was chosen based on its popularity and favourable energy consumption characteristics [42]. In this method, raw materials such as limestone and clay are blended, pulverized, and then subjected to kiln firing. The dry method has gained prominence in the industry due to its energy efficiency and relatively lower environmental emissions compared to other cement production methods [43].



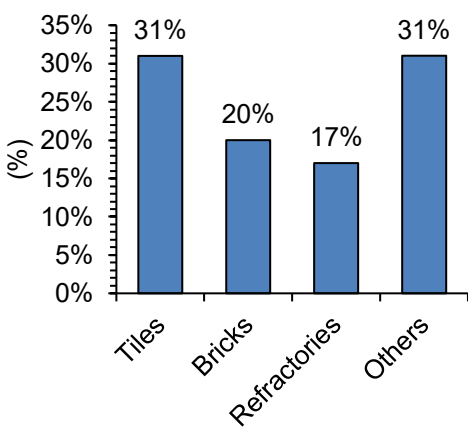
(a) Global metals production by type in 2021



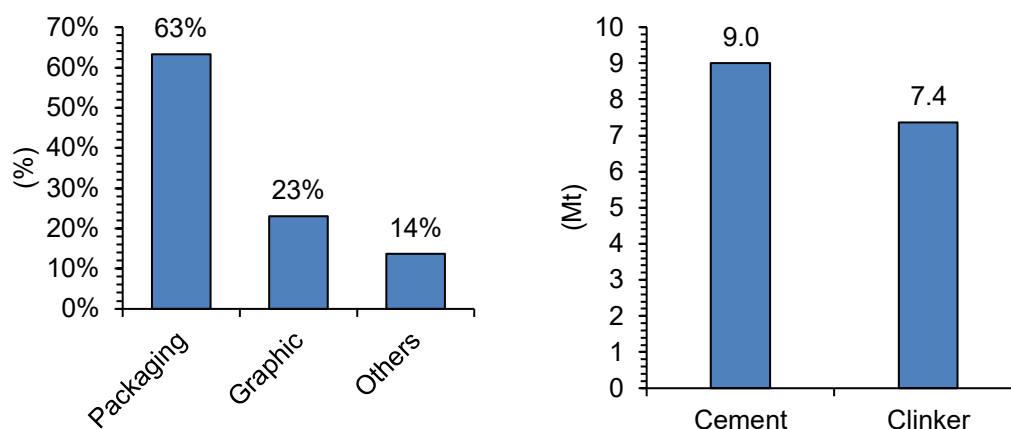
(b) Glass global production by type in 2018



(c) Chemicals U.S. production by type in 2019



(d) Ceramics EU production value by type in 2020



(e) Paper global production by type in 2021

(f) Cement and clinker global production in 2021

**Figure 35 Global and regional production by product type for selected sectors. (a) Metals, (b) Glass, (c) Chemicals, (d) Ceramics, (e) Paper and (f) Cement. Compiled from [22–29]**

In summary, this section focused on product selection within the 6 industries. The product selection process involves using global production data or major producing country volumes to determine the main products. For route selection, the prevalent production method is analysed. Figure 36 showcases the main products and production routes across the six FIs as well as highlighting the selected ones.

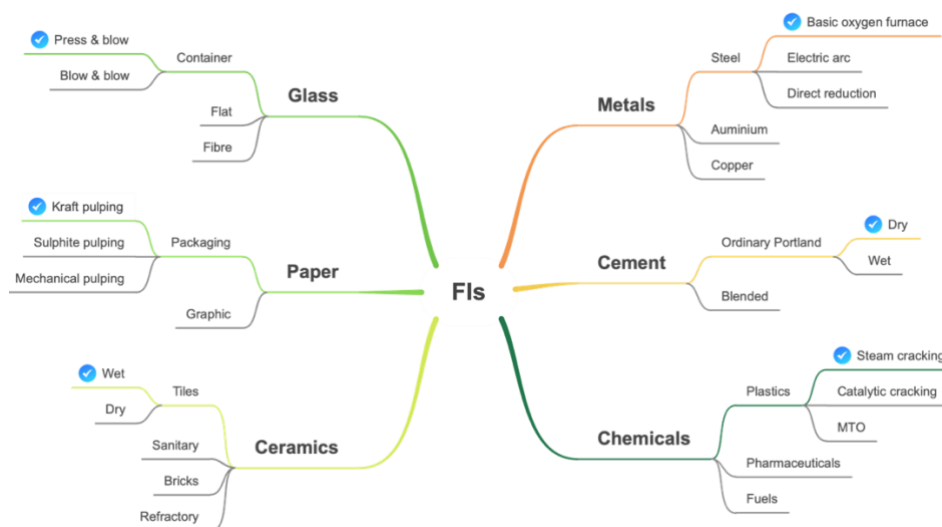


**Figure 36 Identified main products and production routes across the 6 foundation industries**

#### 5.4.1.7 Process maps

Following the product and route selection, process maps were created to track the production cycle from raw material preparation to processing, transformation, and finishing stages in each industry as presented in Figure 37. In total, 37 processes have been identified. This information laid the foundation for further analysis, evaluation, and exploration of common processes and their energy and environmental implications.

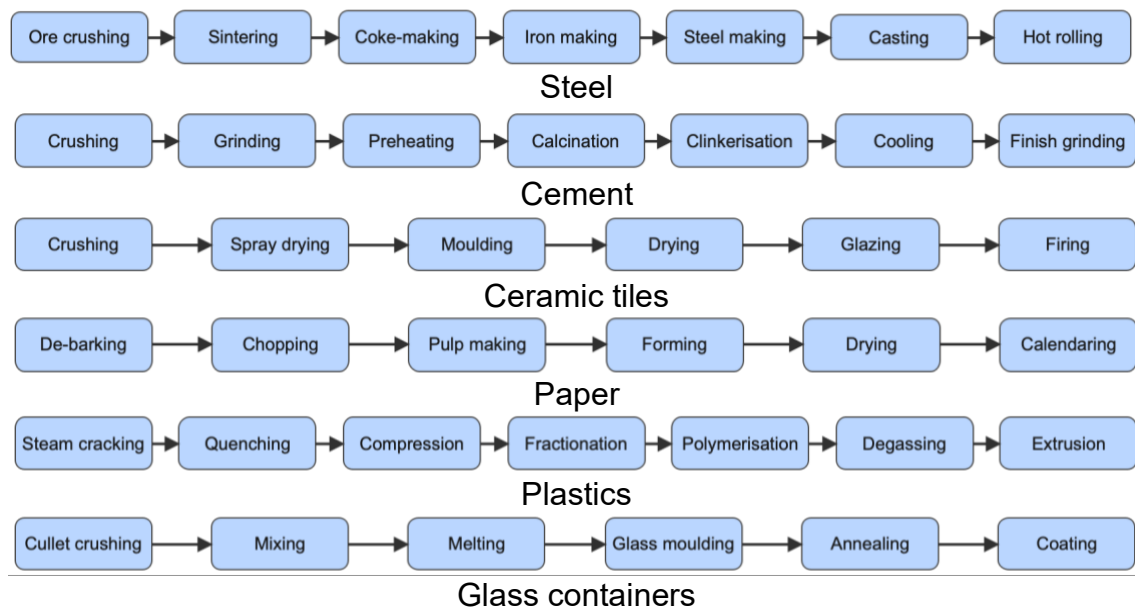


**Figure 37 Process flow map for the selected products within the 6 foundation industries. Data from [44–48]**

#### 5.4.2 Commonality matrix

This step was instigated by classifying the production processes of the selected products using the three-tier method. In which the processes are depicted in terms of their principle, the outcome and the equipment used. The classification of processes is presented in Table D.1 in Appendix D.

The commonality matrix was developed to analyse the shared processes across the studied industries. The subsequent phase included populating the matrix where the identified 37 processes are placed both vertically and horizontally, as presented in Figure 38. Each process is rated against others in terms of common principles, outcomes, and equipment. A score of 1 is assigned for common

principles, 2 for common outcomes, and 3 for common equipment. This scoring system allowed for an assessment of the level of commonality among the processes. The matrix provided a visual representation of the interconnections and similarities between processes across the different industries, highlighting the areas of overlap and potential collaboration.

|    |                                               | 1            | 2         | 3           | 4           | 5            | 6                  | 7           | 8                 | 9                 | 10             | 11              | 12              | 13               | 14           | 15               | 16             | 17      | 18             | 19         | 20       | 21          | 22            | 23           | 24          | 25             | 26        | 27          | 28            | 29             | 30        | 31        | 32              | 33           | 34            | 35             | 36        | 37      |   |   |   |
|----|-----------------------------------------------|--------------|-----------|-------------|-------------|--------------|--------------------|-------------|-------------------|-------------------|----------------|-----------------|-----------------|------------------|--------------|------------------|----------------|---------|----------------|------------|----------|-------------|---------------|--------------|-------------|----------------|-----------|-------------|---------------|----------------|-----------|-----------|-----------------|--------------|---------------|----------------|-----------|---------|---|---|---|
|    | 1 - Principle<br>2 - Outcome<br>3 - Equipment | Ore crushing | Sintering | Coke-making | Iron making | Steel making | Continuous casting | Hot rolling | Raw meal crushing | Raw meal grinding | Clinkerisation | Clinker cooling | Cement grinding | Ceramic crushing | Spray drying | Ceramic pressing | Ceramic drying | Glazing | ceramic firing | De-barking | Chopping | Pulp making | Paper forming | Paper drying | Calendering | Steam cracking | Quenching | Compression | Fractionation | Polymerisation | Degassing | Extrusion | Cullet crushing | Glass mixing | Glass melting | Glass moulding | Annealing | Coating |   |   |   |
| 1  | Ore crushing                                  | Metals       | 0         | 0           | 0           | 0            | 0                  | 0           | 3                 | 2                 | 0              | 0               | 2               | 2                | 0            | 0                | 0              | 0       | 0              | 0          | 2        | 0           | 0             | 0            | 0           | 0              | 0         | 0           | 0             | 0              | 0         | 0         | 2               | 0            | 0             | 0              | 0         | 0       |   |   |   |
| 2  | Sintering                                     | Steel        | 0         | 1           | 1           | 1            | 0                  | 0           | 0                 | 0                 | 1              | 0               | 0               | 0                | 0            | 0                | 0              | 0       | 1              | 0          | 0        | 0           | 0             | 0            | 0           | 0              | 1         | 0           | 0             | 0              | 0         | 0         | 0               | 0            | 1             | 0              | 0         | 0       |   |   |   |
| 3  | Coke-making                                   | BOF          | 0         | 1           | 1           | 1            | 0                  | 0           | 0                 | 0                 | 1              | 0               | 0               | 0                | 0            | 0                | 0              | 0       | 1              | 0          | 0        | 0           | 0             | 0            | 0           | 0              | 1         | 0           | 0             | 0              | 0         | 0         | 0               | 0            | 0             | 1              | 0         | 0       | 0 |   |   |
| 4  | Iron making                                   |              | 0         | 1           | 1           | 2            | 0                  | 0           | 0                 | 0                 | 1              | 0               | 0               | 0                | 0            | 0                | 0              | 1       | 0              | 0          | 0        | 0           | 0             | 0            | 0           | 1              | 0         | 0           | 0             | 0              | 0         | 0         | 0               | 0            | 1             | 0              | 0         | 0       | 0 |   |   |
| 5  | Steel making                                  |              | 0         | 1           | 1           | 2            | 0                  | 0           | 0                 | 0                 | 1              | 0               | 0               | 0                | 0            | 0                | 0              | 1       | 0              | 0          | 0        | 0           | 0             | 0            | 0           | 1              | 0         | 0           | 0             | 0              | 0         | 0         | 0               | 0            | 1             | 0              | 0         | 0       | 0 |   |   |
| 6  | Continuous casting                            |              | 0         | 0           | 0           | 0            | 0                  | 0           | 0                 | 0                 | 0              | 0               | 0               | 0                | 0            | 0                | 0              | 0       | 0              | 0          | 0        | 0           | 0             | 0            | 0           | 0              | 0         | 0           | 0             | 0              | 0         | 0         | 0               | 0            | 0             | 0              | 0         | 0       | 0 |   |   |
| 7  | Hot rolling                                   |              | 0         | 0           | 0           | 0            | 0                  | 0           | 0                 | 0                 | 0              | 0               | 0               | 0                | 1            | 0                | 0              | 0       | 0              | 0          | 0        | 0           | 0             | 0            | 0           | 0              | 0         | 0           | 0             | 0              | 0         | 0         | 0               | 0            | 0             | 1              | 0         | 0       | 0 |   |   |
| 8  | Raw meal crushing                             | Cement       | 3         | 0           | 0           | 0            | 0                  | 0           | 2                 | 0                 | 0              | 2               | 2               | 0                | 0            | 0                | 0              | 0       | 0              | 2          | 0        | 0           | 0             | 0            | 0           | 0              | 0         | 0           | 0             | 0              | 0         | 0         | 2               | 0            | 0             | 0              | 0         | 0       | 0 |   |   |
| 9  | Raw meal grinding                             | Portland     | 2         | 0           | 0           | 0            | 0                  | 0           | 2                 | 0                 | 0              | 3               | 3               | 0                | 0            | 0                | 0              | 0       | 0              | 2          | 0        | 0           | 0             | 0            | 0           | 0              | 0         | 0           | 0             | 0              | 0         | 0         | 3               | 0            | 0             | 0              | 0         | 0       | 0 |   |   |
| 10 | Clinkerisation                                | Dry          | 0         | 1           | 1           | 1            | 0                  | 0           | 0                 | 0                 | 0              | 0               | 0               | 0                | 0            | 0                | 0              | 1       | 0              | 0          | 0        | 0           | 0             | 0            | 0           | 1              | 0         | 0           | 0             | 0              | 0         | 0         | 0               | 0            | 1             | 0              | 0         | 0       | 0 |   |   |
| 11 | Clinker cooling                               |              | 0         | 0           | 0           | 0            | 0                  | 0           | 0                 | 0                 | 0              | 0               | 0               | 0                | 0            | 0                | 0              | 0       | 0              | 0          | 0        | 0           | 0             | 0            | 0           | 0              | 1         | 0           | 0             | 0              | 0         | 0         | 0               | 0            | 0             | 0              | 1         | 0       | 0 |   |   |
| 12 | Cement grinding                               |              | 2         | 0           | 0           | 0            | 0                  | 0           | 2                 | 3                 | 0              | 0               | 3               | 0                | 0            | 0                | 0              | 0       | 2              | 0          | 0        | 0           | 0             | 0            | 0           | 0              | 0         | 0           | 0             | 0              | 0         | 0         | 3               | 0            | 0             | 0              | 0         | 0       | 0 |   |   |
| 13 | Ceramic crushing                              | Ceramics     | 2         | 0           | 0           | 0            | 0                  | 0           | 2                 | 3                 | 0              | 0               | 3               | 0                | 0            | 0                | 0              | 0       | 2              | 0          | 0        | 0           | 0             | 0            | 0           | 0              | 0         | 0           | 0             | 0              | 0         | 0         | 3               | 0            | 0             | 0              | 0         | 0       | 0 |   |   |
| 14 | Spray drying                                  | Tiles        | 0         | 0           | 0           | 0            | 0                  | 0           | 0                 | 0                 | 0              | 0               | 0               | 0                | 0            | 0                | 2              | 0       | 0              | 0          | 0        | 0           | 0             | 0            | 2           | 0              | 0         | 0           | 0             | 0              | 0         | 0         | 0               | 0            | 0             | 0              | 0         | 0       | 0 | 0 |   |
| 15 | Ceramic pressing                              | Wet          | 0         | 0           | 0           | 0            | 0                  | 1           | 0                 | 0                 | 0              | 0               | 0               | 0                | 0            | 0                | 0              | 0       | 0              | 0          | 0        | 0           | 0             | 0            | 0           | 0              | 0         | 0           | 0             | 0              | 0         | 0         | 0               | 0            | 0             | 2              | 0         | 0       | 0 |   |   |
| 16 | Ceramic drying                                |              | 0         | 0           | 0           | 0            | 0                  | 0           | 0                 | 0                 | 0              | 0               | 0               | 0                | 2            | 0                | 0              | 0       | 0              | 0          | 0        | 0           | 0             | 2            | 0           | 0              | 0         | 0           | 0             | 0              | 0         | 0         | 0               | 0            | 0             | 0              | 0         | 0       | 0 | 0 |   |
| 17 | Glazing                                       |              | 0         | 0           | 0           | 0            | 0                  | 0           | 0                 | 0                 | 0              | 0               | 0               | 0                | 0            | 0                | 0              | 0       | 0              | 0          | 0        | 0           | 0             | 0            | 0           | 0              | 0         | 0           | 0             | 0              | 0         | 0         | 0               | 0            | 0             | 0              | 0         | 0       | 0 |   |   |
| 18 | ceramic firing                                |              | 0         | 1           | 1           | 1            | 1                  | 0           | 0                 | 0                 | 1              | 0               | 0               | 0                | 0            | 0                | 0              | 0       | 0              | 0          | 0        | 0           | 0             | 0            | 1           | 0              | 0         | 0           | 0             | 0              | 0         | 0         | 0               | 1            | 0             | 0              | 0         | 0       | 0 | 0 |   |
| 19 | De-barking                                    | Paper        | 0         | 0           | 0           | 0            | 0                  | 0           | 0                 | 0                 | 0              | 0               | 0               | 0                | 0            | 0                | 0              | 0       | 0              | 0          | 0        | 0           | 0             | 0            | 0           | 0              | 0         | 0           | 0             | 0              | 0         | 0         | 0               | 0            | 0             | 0              | 0         | 0       | 1 | 0 |   |
| 20 | Chopping                                      | Packaging    | 2         | 0           | 0           | 0            | 0                  | 0           | 2                 | 2                 | 0              | 0               | 2               | 2                | 0            | 0                | 0              | 0       | 0              | 0          | 0        | 0           | 0             | 0            | 0           | 0              | 0         | 0           | 0             | 0              | 0         | 0         | 2               | 0            | 0             | 0              | 0         | 0       | 0 | 0 |   |
| 21 | Pulp making                                   | Kraft        | 0         | 0           | 0           | 0            | 0                  | 0           | 0                 | 0                 | 0              | 0               | 0               | 0                | 0            | 0                | 0              | 0       | 0              | 0          | 0        | 0           | 0             | 0            | 0           | 0              | 0         | 0           | 0             | 0              | 0         | 0         | 0               | 0            | 0             | 0              | 0         | 0       | 0 | 0 |   |
| 22 | Paper forming                                 |              | 0         | 0           | 0           | 0            | 0                  | 0           | 0                 | 0                 | 0              | 0               | 0               | 0                | 0            | 0                | 0              | 0       | 0              | 0          | 0        | 0           | 0             | 0            | 0           | 1              | 0         | 0           | 0             | 0              | 0         | 1         | 0               | 0            | 0             | 0              | 0         | 0       | 0 | 0 |   |
| 23 | Paper drying                                  |              | 0         | 0           | 0           | 0            | 0                  | 0           | 0                 | 0                 | 0              | 0               | 0               | 0                | 2            | 0                | 2              | 0       | 0              | 0          | 0        | 0           | 0             | 0            | 0           | 0              | 0         | 0           | 0             | 0              | 0         | 0         | 0               | 0            | 0             | 0              | 0         | 0       | 0 | 0 |   |
| 24 | Calendering                                   |              | 0         | 0           | 0           | 0            | 0                  | 0           | 0                 | 0                 | 0              | 0               | 0               | 0                | 0            | 0                | 0              | 0       | 0              | 0          | 0        | 0           | 1             | 0            | 0           | 0              | 0         | 0           | 0             | 0              | 0         | 1         | 0               | 0            | 0             | 0              | 0         | 0       | 0 | 0 |   |
| 25 | Steam cracking                                | Chemicals    | 0         | 1           | 1           | 1            | 1                  | 0           | 0                 | 0                 | 1              | 0               | 0               | 0                | 0            | 0                | 0              | 1       | 0              | 0          | 0        | 0           | 0             | 0            | 0           | 0              | 0         | 0           | 0             | 0              | 0         | 0         | 0               | 0            | 1             | 0              | 0         | 0       | 0 | 0 |   |
| 26 | Quenching                                     | Plastics     | 0         | 0           | 0           | 0            | 0                  | 0           | 0                 | 0                 | 1              | 0               | 0               | 0                | 0            | 0                | 0              | 0       | 0              | 0          | 0        | 0           | 0             | 0            | 0           | 0              | 0         | 0           | 0             | 0              | 0         | 0         | 0               | 0            | 0             | 0              | 1         | 0       | 0 | 0 |   |
| 27 | Compression                                   | Steam        | 0         | 0           | 0           | 0            | 0                  | 0           | 0                 | 0                 | 0              | 0               | 0               | 0                | 0            | 0                | 0              | 0       | 0              | 0          | 0        | 0           | 0             | 0            | 0           | 0              | 0         | 0           | 0             | 0              | 0         | 0         | 0               | 0            | 0             | 0              | 0         | 0       | 0 | 0 |   |
| 28 | Fractionation                                 |              | 0         | 0           | 0           | 0            | 0                  | 0           | 0                 | 0                 | 0              | 0               | 0               | 0                | 0            | 0                | 0              | 0       | 0              | 0          | 0        | 0           | 0             | 0            | 0           | 0              | 0         | 0           | 0             | 0              | 0         | 0         | 0               | 0            | 0             | 0              | 0         | 0       | 0 | 0 |   |
| 29 | Polymerisation                                |              | 0         | 0           | 0           | 0            | 0                  | 0           | 0                 | 0                 | 0              | 0               | 0               | 0                | 0            | 0                | 0              | 0       | 0              | 0          | 0        | 0           | 0             | 0            | 0           | 0              | 0         | 0           | 0             | 0              | 0         | 0         | 0               | 0            | 0             | 0              | 0         | 0       | 0 | 0 |   |
| 30 | Degassing                                     |              | 0         | 0           | 0           | 0            | 0                  | 0           | 0                 | 0                 | 0              | 0               | 0               | 0                | 0            | 0                | 0              | 0       | 0              | 0          | 0        | 0           | 0             | 0            | 0           | 0              | 0         | 0           | 0             | 0              | 0         | 0         | 0               | 0            | 0             | 0              | 0         | 0       | 0 | 0 |   |
| 31 | Extrusion                                     |              | 0         | 0           | 0           | 0            | 0                  | 0           | 0                 | 0                 | 0              | 0               | 0               | 0                | 0            | 0                | 0              | 0       | 0              | 0          | 0        | 0           | 0             | 1            | 0           | 1              | 0         | 0           | 0             | 0              | 0         | 0         | 0               | 0            | 0             | 0              | 0         | 0       | 0 | 0 | 0 |
| 32 | Cullet crushing                               | Glass        | 2         | 0           | 0           | 0            | 0                  | 0           | 2                 | 3                 | 0              | 0               | 3               | 3                | 0            | 0                | 0              | 0       | 0              | 2          | 0        | 0           | 0             | 0            | 0           | 0              | 0         | 0           | 0             | 0              | 0         | 0         | 0               | 0            | 0             | 0              | 0         | 0       | 0 | 0 | 0 |
| 33 | Glass mixing                                  | Container    | 0         | 0           | 0           | 0            | 0                  | 0           | 0                 | 0                 | 0              | 0               | 0               | 0                | 0            | 0                | 0              | 0       | 0              | 0          | 0        | 0           | 0             | 0            | 0           | 0              | 0         | 0           | 0             | 0              | 0         | 0         | 0               | 0            | 0             | 0              | 0         | 0       | 0 | 0 |   |
| 34 | Glass melting                                 | Press        | 0         | 1           | 1           | 1            | 1                  | 0           | 0                 | 0                 | 1              | 0               | 0               | 0                | 0            | 0                | 0              | 0       | 1              | 0          | 0        | 0           | 0             | 0            | 0           | 0              | 1         | 0           | 0             | 0              | 0         | 0         | 0               | 0            | 0             | 0              | 0         | 0       | 0 | 0 | 0 |
| 35 | Glass moulding                                |              | 0         | 0           | 0           | 0            | 0                  | 1           | 0                 | 0                 | 0              | 0               | 0               | 0                | 2            | 0                | 0              | 0       | 0              | 0          | 0        | 0           | 0             | 0            | 0           | 0              | 0         | 0           | 0             | 0              | 0         | 0         | 0               | 0            | 0             | 0              | 0         | 0       | 0 | 0 |   |
| 36 | Annealing                                     |              | 0         | 0           | 0           | 0            | 0                  | 0           | 0                 | 0                 | 1              | 0               | 0               | 0                | 0            | 0                | 0              | 0       | 0              | 0          | 0        | 0           | 0             | 0            | 0           | 1              | 0         | 0           | 0             | 0              | 0         | 0         | 0               | 0            | 0             | 0              | 0         | 0       | 0 | 0 | 0 |
| 37 | Coating                                       |              | 0         | 0           | 0           | 0            | 0                  | 0           | 0                 | 0                 | 0              | 0               | 0               | 0                | 0            | 0                | 0              | 0       | 1              | 0          | 0        | 0           | 0             | 0            | 0           | 0              | 0         | 0           | 0             | 0              | 0         | 0         | 0               | 0            | 0             | 0              | 0         | 0       | 0 | 0 |   |

Figure 38 Commonality matrix

### 5.4.3 Processes analysis

Out of the 37 processes investigated, 18 were identified as common processes based on the three aspects of principle, outcome, and equipment. All of which ranked among the top intensive processes in terms of both electrical and thermal energy consumption as well as CO<sub>2</sub> emissions, results presented in Table 18. This emphasises the diverse energy demands and environmental impacts of these processes. Moreover, the possible size of the prize that could be acquired by sharing knowledge across sectors.

**Table 18 Top common processes energy and emissions intensiveness analysis, data acquired from [48–60]**

|                   | Top electrical | Top thermal | Top CO2 emitter |
|-------------------|----------------|-------------|-----------------|
| Ore crushing      | ✓              |             |                 |
| Raw meal crushing | ✓              |             |                 |
| Ceramic crushing  | ✓              |             |                 |
| Cullet crushing   | ✓              |             |                 |
| Raw meal grinding | ✓              |             |                 |
| Cement grinding   | ✓              |             |                 |
| Chopping          | ✓              |             |                 |
| Iron making       |                | ✓           | ✓               |
| Steelmaking       |                |             | ✓               |
| Sintering         | ✓              | ✓           | ✓               |
| Coke-making       |                | ✓           | ✓               |
| Clinkerisation    |                | ✓           | ✓               |
| Ceramic firing    | ✓              | ✓           | ✓               |
| Steam cracking    | ✓              | ✓           | ✓               |
| Glass melting     | ✓              | ✓           | ✓               |
| Spray drying      | ✓              | ✓           | ✓               |
| Ceramic drying    |                | ✓           | ✓               |
| Paper drying      | ✓              | ✓           | ✓               |

Regarding the commonality of principles, Pyroprocessing, in which materials are subjected to high temperatures to instigate a chemical or physical change, emerged as predominantly common, found across all sectors except for paper. This indicates its widespread application and importance in various industries. On the other hand, the most shared outcome was the production of dried products, a recurring theme observed in both ceramics and paper sectors in which moisture is removed from intermediate products. Furthermore, reduction in material size, an outcome that requires mechanical force to facilitate handling and processing, occurred in all industries except chemicals. In terms of machinery, crushers and grinding mills were identified as the most frequently utilised equipment, prominently featured in all industries except chemicals and paper. Their prevalence underscores their crucial role in these sectors and their

significant impact on environmental impact. The 18 processes along with their corresponding aspects are illustrated in Figure 39.

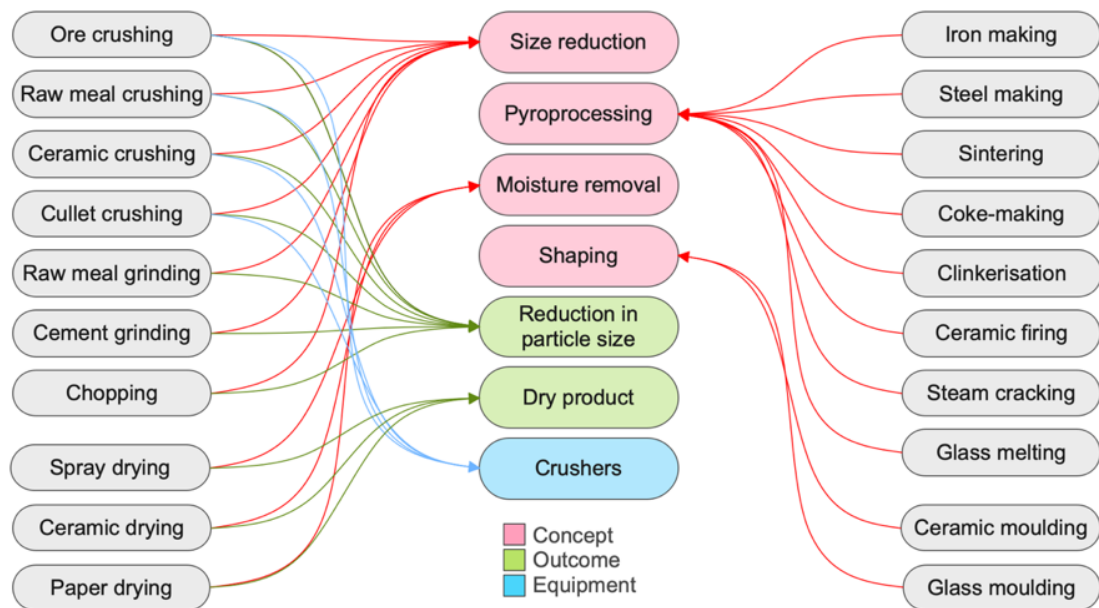


**Figure 39 Common processes and their associated common principles, outcomes, and equipment**

Practitioners across different sectors should take note of the identified common processes, as they represent critical areas where collaborative efforts and knowledge-sharing could lead to substantial efficiency gains. By leveraging shared insights and best practices, practitioners have the potential to significantly reduce resource consumption and environmental footprints in their respective industries. For researchers, these findings highlight the need for further investigations into specific technologies and strategies that can enhance the sustainability of these common processes. Exploring innovative approaches to improve the energy efficiency and environmental performance of these intensive processes could yield breakthroughs that benefit not only individual industries but also contribute to broader sustainability goals.

#### 5.4.4 Abatement options

##### 5.4.4.1 Pyroprocessing

Pyroprocessing is a major processing technology in the FIs. With high heat input being a major requirement in manufacturing but also a source of concern due to

the high energy required to provide it, multiple actions are stated to mitigate the energy consumption of such a process. These are available as different features targeted to each industry or technology. For instance, a Blast furnace could benefit from pulverised coal injection resulting in a 3.6% energy reduction [61]. On the other hand, altering steam flow rate and cooling water temperature reduces the energy consumption of steam crackers by 13% [62]. However, a few improvements could also apply to more than one industry. A preheating tunnel in steel production can save up to 0.22 GJ/t of energy [63]. In cement, a 6-stage preheater can save up to 1.27 GJ/t of energy compared to a 1-stage preheater [64]. The preheating of glass prior to melting however has only recently gained traction despite its energy-saving potential [65,66]. Another aspect encompassing pyroprocessing is surface heat loss. Insulation plates on glass melting furnaces reduce thermal losses [67] while improving cement kiln refractoriness can save up to 0.6 GJ/t of thermal energy [68]. Furthermore, heat recovery technologies are employed to convert waste heat into useful energy. It does not reduce the pyroprocessing energy specifically, but since the recovered energy could be utilised elsewhere in the process, it lowers the overall energy consumption per unit product. It has been used in cement kilns to recover up to 5% of waste heat [69]. It has also been recorded in blast furnaces, improving efficiency by 3.1% [70] and in ceramics firing kilns in which efficiency was improved by 11% [71]. Moreover, increasing evidence demonstrates that transitioning from fossil fuel consumption to electric technologies reduces both costs and emissions [72]. In the scenario of firing ceramics, furnace electrification could be a viable alternative for reducing gas emissions, especially for large kilns producing bricks and tiles [73,74]. During cement manufacturing, switching from a coal-fired calciner system to an electrically powered calciner can lead to a reduction of 78% in CO<sub>2</sub> emissions [75]. However, the prominence of electrification comes into play when the source of electrical energy is derived from renewable sources. These findings indicate a need for a thorough analysis of intersected practices and their applicability to be functional to other sectors.

#### **5.4.4.2 Drying**

The drying of intermediate products is one of the most energy-intensive processes. 67% of the total energy required to produce paper [76] and 45% of ceramics production energy [77] is due to drying. In the case of paper drying, it is conventionally accomplished by a steam-heated roller. Enhancing heat recovery techniques for the heated rollers can lead to a potential 16% decrease in energy usage. This outcome corresponds to a consequent reduction of 12% in emissions [78]. Furthermore, emerging technologies in microwave drying have shown energy reductions of up to 12% [79]. A similar trend has been observed in the ceramics industry where infrared has been successfully used to dry ceramics with 4 times less power [80].

#### **5.4.4.3 Crushing and grinding**

Fine particle size is crucial to enable smooth handling and subsequent production stages like burning or mixing. Cement raw material crushing and grinding represents a significant portion, accounting for 71% of the total consumed electrical power [81]. The adoption of vertical roller mills in raw material grinding has demonstrated a notable reduction of 25% in energy consumption and a 57% decrease in CO<sub>2</sub> emissions compared to traditional ball mills [82,83]. For raw material crushing, cone crushers are identified as more efficient than other alternatives [84]. However, there appears to be a limited focus on new or emerging technologies specifically aimed at further reducing energy consumption in these processes.

### **5.5 Conclusion and future work**

Foundation industries play a pivotal role in global manufacturing, providing essential materials for various sectors. To enhance sustainability and resource efficiency, this study delved into the commonality of processes across different sectors. The research involved a thorough examination of 37 processes, assessing their principles, outcomes, and equipment. By using an adapted DSM, 18 processes were identified as common across the 6 sectors in question which were further analysed based on their energy and CO<sub>2</sub> emission intensities. The key findings shed light on the prevalence of these processes as well as

accentuate the diverse energy prerequisites and environmental consequences of these operations. Furthermore, it highlights the potential significant benefits achievable by cross-sector knowledge sharing. Pyroprocessing emerged as a prominent principle, widely applied across most sectors except paper. Additionally, the production of dried products was a common outcome observed in the ceramics and paper industries. Crushers and grinding mills were identified as frequently utilised machinery.

Moreover, various abatement options have been identified to address energy consumption and CO<sub>2</sub> emissions associated with these common processes. These options range from efficient heat recovery systems to the utilisation of alternative fuels and electrification. Interestingly, certain sectors seem to have more mature solutions in place for tackling these challenges, while others have not extensively explored these strategies. This discrepancy underscores the valuable cross-sector knowledge exchange that could take place. By sharing successful practices and technologies across industries, sectors can accelerate their sustainability efforts and reduce the need to reinvent solutions already in existence. This cooperative approach could lead to more efficient adoption of established technologies, ultimately contributing to a more sustainable industrial landscape.

The findings align with the Sustainable Development Goals (SDGs), supporting sustainable industrialisation, responsible consumption and production, and climate action. This analysis equips stakeholders with valuable information to allocate resources effectively, prioritise improvement efforts, and adopt sustainable practices. Furthermore, it offers a basis for benchmarking and best practice adoption, driving the industry's transition towards sustainable manufacturing.

Future work will extend the analysis to encompass all products within each sector, exploring additional potential knowledge exchange opportunities among industries. Furthermore, by incorporating additional layers, such as considering process mechanisms, the potential for unveiling further shared characteristics is

heightened. This holistic approach will streamline the identification of optimal practices, nurturing sustainable methodologies across diverse sectors.

## **5.6 Contribution of Paper to Thesis Objectives**

This paper contributes directly to Objective 4 by identifying and analysing shared manufacturing processes across the foundation industries, thereby enabling cross-sectoral benchmarking and targeted sustainability interventions. Through an adapted Dependency Structure Matrix, 37 processes were mapped and evaluated based on common principles, outcomes, and equipment. This resulted in the identification of 18 high-impact shared processes, many of which are among the most energy- and emission-intensive operations across sectors.

The study contributes several key insights. First, it introduces a structured method for uncovering technical commonalities between sectors, allowing stakeholders to prioritise improvements where sectoral overlap exists. Second, it demonstrates that processes like pyroprocessing, drying, and grinding are not only widespread but also central to sustainability challenges, offering clear targets for coordinated abatement strategies. Third, it highlights the uneven distribution of technological maturity and abatement solutions across sectors, reinforcing the value of knowledge transfer and shared innovation pathways.

By revealing these overlaps and opportunities, the study supports the thesis's aim of developing process-focused tools that are adaptable across industrial contexts. It shifts the focus from isolated sectoral actions to a more integrated perspective, aligning with the thesis direction of enabling practical and transferable solutions for sustainable manufacturing.

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## **6 A multi-criteria similarity-based framework for sustainability assessment of manufacturing processes in foundation industries <sup>7</sup>**

### **6.1 Paper Linkage to Research Aim and Objectives**

This chapter addresses Objective 5 of the thesis, which was to enable cross-industry benchmarking and informed decision-making by integrating sustainability metrics into a similarity-based approach. It presents a novel framework, SIMSA (Similarity-based Sustainability Assessment), designed to support comparative analysis of manufacturing processes within and across sectors. The rationale for this study stems from limitations in existing benchmarking approaches, which are often restricted to specific sectors and lack detail at the unit process level.

The chapter builds on earlier insights regarding benchmarking and the use of indicators (Chapters 3 and 4), as well as shared processes (Chapter 5), by presenting a structured method to quantify how closely different processes align in terms of sustainability performance. Unlike conventional ranking-based benchmarks, this approach focuses on relational performance by evaluating the similarity between processes rather than their absolute scores, enabling benchmarking across sectoral boundaries.

This contributes directly to the thesis goal of advancing scalable, data-driven sustainability benchmarking methods tailored to the complexity and diversity of process manufacturing systems.

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<sup>7</sup> Z. Sherif and K. Salonitis, "A multi-criteria similarity-based framework for sustainability assessment of manufacturing processes in Resource-Intensive Industries," 2025 (To be submitted).

## 6.2 Introduction

Process industries such as metals, cement, paper and chemicals significantly impact the environmental, economic and social sustainability dimensions due to their resource-intensive nature [1–3]. Addressing sustainability in these sectors is increasingly important due to regulatory pressures, stakeholder demands and the broader global push towards sustainable industrial practices [4,5]. Therefore, sustainability benchmarking frameworks and methods have become essential tools for evaluating and comparing manufacturing processes across these industries [6–9].

Benchmarking provides a structured approach for comparing performance across manufacturing processes and identifying areas for improvement [10]. Benchmarking typically relies on Key Performance Indicators (KPIs) that reflect environmental, economic, or social impacts, often referenced against best practice benchmarks or sectoral standards such as Best Available Techniques (BAT) [11]. While widely used, traditional benchmarking approaches are often restricted as they tend to be sector-specific, which limits the ability to transfer knowledge or best practices across industries. Moreover, they frequently rely on subjective weighting of indicators, which introduces bias and reduces transparency and reproducibility [12,13]. This highlights the need for more integrated and objective methods for sustainability assessment.

This study addresses this gap by introducing a similarity-based benchmarking framework that evaluates how closely processes resemble one another in terms of sustainability performance. The approach shifts focus from ranking processes in isolation to analysing relative differences between them, enabling more meaningful cross-sectoral comparison while retaining process-level granularity. The concept of process similarity is well established in product-centric manufacturing for optimising production efficiency through shared resources and workflows [14]. Its extension to sustainability benchmarking can support the identification of common challenges and transferable best practices across sectors, offering potential for efficiency gains, emissions reduction and circular economy initiatives.

The proposed framework uses ratio-based normalisation of process KPIs relative to BAT values, ensuring comparability across indicators with different units and performance directions. Sustainability aspects are aggregated using an objective Multi-Criteria Decision Analysis (MCDA) method that combines Monte Carlo simulation with the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). This enables the generation of probabilistic weights without expert input, improving the reproducibility and robustness of the analysis [15]. It also allows the analysis to be conducted at different levels of granularity, either at the individual KPI level or at the broader sustainability dimension level, depending on the decision-making context.

By applying this framework across multiple process industries, the study offers a new method for assessing sustainability performance, supporting both benchmarking and the identification of opportunities for process-level improvement and inter-industry collaboration.

### **6.2.1 Background and Context**

Sustainability assessments are critical for promoting responsible practices within manufacturing industries. Most studies adopt the triple bottom line (TBL) framework, assessing environmental, economic, and social dimensions through tools such as Life Cycle Assessment methods, Material Flow Analysis (MFA), and indicator-based schemes aligned with ISO 14001 and the Global Reporting Initiative (GRI) [16–18]. While effective within individual sectors, these methods often lack comparability across industries due to differences in scope, units, and performance metrics.

Benchmarking based on BAT provides clear performance targets for resource efficiency and emissions reduction, particularly in energy-intensive sectors such as cement and steel [19]. However, existing BAT frameworks are typically sector-specific and primarily focused on environmental performance, particularly emissions and resource use [20]. This narrow scope limits their ability to capture broader sustainability dimensions and reduces their utility for identifying shared opportunities or transferring knowledge across industries[9,21]. Cross-sectoral benchmarking offers a pathway to overcome this limitation. It enables the

discovery of mutual sustainability opportunities and performance improvements by comparing similar processes across different industrial contexts [22]. Such exchanges form the foundation of industrial symbiosis, a key strategy for circular economy implementation [23]. While case studies have demonstrated that by-products, waste heat and intermediate outputs can be shared across sectors [24,25], there remains a lack of systematic methods to evaluate and compare their sustainability performance, particularly at the process level, where detailed benchmarking is essential to identify transferrable practices.

Two core methodological challenges arise from this context. The first concerns how to evaluate performance across multiple sustainability dimensions transparently and practically. Incorporating indicators from environmental, economic and social domains introduces trade-offs between conflicting objectives [26,27]. For instance, a process may reduce emissions while increasing cost or reducing productivity. MCDA methods, such as the Analytic Hierarchy Process (AHP), are commonly used to integrate such trade-offs into a single performance score [28–30]. However, conventional implementations often rely on subjective weightings derived from expert judgment, which introduces bias and reduces reproducibility [31,32]. Recent work has addressed this by applying objective weighting techniques based on statistical or probabilistic methods, including entropy, Traditional CRiteria Importance Through Intercriteria Correlation (CRITIC) based weights and Monte Carlo simulations [15,33,34], improving the robustness of sustainability assessments.

The second challenge relates to how benchmarking is operationalised. While methods exist that consider a holistic sustainability viewpoint [35–37], they mostly focus on ranking processes independently based on performance scores but offer limited insight into how these processes relate to one another across or within sectors [38,39]. As highlighted by Miller et al. [40], benchmarking approaches that focus solely on functional performance may yield precise comparisons but often lack strategic perspective. Conversely, strategic benchmarking tends to be more abstract and less actionable at the process level. To address this, integrating process similarity into sustainability benchmarking

offers a more relational and system-oriented view. Similarity analysis has long been used in manufacturing to cluster product families, simplify operations and enhance production flexibility [41,42], but has rarely been applied in the context of sustainability performance. When used in this way, similarity assessments can identify process clusters with comparable sustainability profiles, enabling cross-sectoral benchmarking and revealing opportunities for shared improvement, resource exchange, and industrial symbiosis.

This study addresses these domains by developing a Similarity-based Sustainability Assessment (SIMSA) framework to benchmark processes within and across sectors. It utilises BAT-relative normalisation, Monte Carlo-based TOPSIS for objective weighting and pairwise process comparisons. The approach enables detailed and reproducible assessments across multiple sustainability dimensions while supporting the identification of transferable practices and opportunities for industrial symbiosis. Process industries were targeted due to their high resource demand, significant environmental footprint and notable economic and social impacts [43,44]. Furthermore, those industries share common manufacturing processes such as heating, grinding, drying and forming [45], underscoring the potential and necessity for cross-sectoral benchmarking.

## **6.3 Methodology**

The methodology section details the development of the SIMSA framework, an objective and structured approach designed specifically for sustainability benchmarking in manufacturing industries. The development is accomplished through sequential and literature-supported methodological stages.

### **6.3.1 Literature-Based KPI Selection Methodology**

A structured, literature-driven approach was adopted to ensure a comprehensive selection of sustainability KPIs at the manufacturing-process level. Initially, potential KPIs were identified through detailed analysis and review of established sustainability assessment frameworks, benchmarking guidelines and peer-reviewed academic studies. Primary sources included widely recognised

frameworks such as European Union Best Available Techniques Reference Documents (EU-BREF) [46], Global Reporting Initiative (GRI) standards and the Organisation for Economic Co-operation and Development (OECD) recommendations [47]. Subsequently, identified KPIs underwent screening based on explicitly defined criteria aimed at ensuring process-level applicability. KPIs were required to be measurable at the individual process or unit-operation level, quantifiable in clearly defined units and consistently applicable across the selected industries to enable robust cross-sectoral comparisons. Additionally, each KPI had to exhibit a clear directional preference, with clarity on whether improvement corresponds to an increase or a decrease in its value. Established frequency of use within academic and industrial literature further reinforced the practical and theoretical relevance of each KPI.

The final set of KPIs was structured around the widely adopted TBL framework, which includes environmental, economic, and social dimensions [48]. Environmental indicators focus on core operational metrics such as energy consumption, water use, emissions and waste generation. Economic indicators cover disaggregated cost components, as well as productivity, enabling more granular analysis of process efficiency. Social indicators, although more challenging to quantify, include process-level safety incidents, employment stability, noise exposure and exposure to hazardous substances. These reflect practical aspects of worker well-being that are relevant across a wide range of industrial settings. Table 19 summarises the selected KPIs, including their measurement units and directional guidewords ("Reduce" or "Increase"). These guidewords indicate the direction associated with improved sustainability performance. For example, "Reduce" applies to indicators such as emissions or energy use, while "Increase" applies to indicators like productivity or Personal Protective Equipment (PPE) compliance.

The KPI list is not intended to serve as a comprehensive performance management toolkit. Rather, it provides a representative and operationally grounded set of indicators to support meaningful cross-sector comparison and process-level sustainability benchmarking. The set is specific enough to capture

differences at the unit process level while remaining adaptable across sectors and contexts.

**Table 19 Identified KPIs for sustainability benchmarking at the manufacturing-process level**

| Sustainability Dimension | KPI Name                             | Unit                     | Guideword | Source |
|--------------------------|--------------------------------------|--------------------------|-----------|--------|
| Environmental            | Electrical Energy Consumption        | kWh / ton                | Reduce    | [49]   |
|                          | Thermal Energy Consumption           | GJ / ton                 | Reduce    | [49]   |
|                          | Energy recovered                     | %                        | Increase  | [50]   |
|                          | CO <sub>2</sub> Emissions            | kg CO <sub>2</sub> / ton | Reduce    | [51]   |
|                          | Waste generation                     | kg waste / ton           | Reduce    | [52]   |
|                          | Water Use                            | m <sup>3</sup> / ton     | Reduce    | [53]   |
| Economic                 | Energy Cost                          | Cost / ton               | Reduce    | [54]   |
|                          | Material Cost                        | Cost / ton               | Reduce    | [54]   |
|                          | Maintenance Cost                     | Cost / ton               | Reduce    | [55]   |
|                          | Labor Cost                           | Cost / ton               | Reduce    | [55]   |
|                          | Productivity / Capacity              | ton / hour               | Increase  | [56]   |
| Social                   | Occupational Injuries                | Incidents / year         | Reduce    | [57]   |
|                          | Use of Personal Protective Equipment | % of workers per process | Increase  | [57]   |
|                          | Employment Stability                 | % retention / year       | Increase  | [58]   |
|                          | Noise Exposure                       | dB per process           | Reduce    | [58]   |
|                          | Exposure to Hazardous Substances     | kg handled / ton         | Reduce    | [59]   |

### 6.3.2 Data Collection and Benchmarking Sources

Benchmarking and normalisation of KPI values were primarily grounded in established reference values represented by BAT. These can be sourced from diverse authoritative sources, including peer-reviewed academic articles, governmental publications (such as EU-BREFs [46]), specialised environmental databases and industry-specific sustainability reports. These BAT values represent optimal sustainability performance achievable under contemporary technological and economic conditions, offering a consistent, standardised basis for cross-sectoral normalisation and comparison. However, it is recognised that BAT values may not always be readily available or sufficiently current due to rapid

technological advancements within the industries. Moreover, several crucial KPIs, especially those within the social sustainability dimension, lack clear governance or established reference benchmarks within existing standardisation frameworks. Nevertheless, clear target reference values must be defined for each sustainability KPI to ensure robust and consistent normalisation. Therefore, alternative practical "best-in-class" values were considered within the SIMSA framework to establish a credible reference value.

In scenarios where authoritative external references are entirely unavailable, reference values can be derived from the best-performing KPI values observed among competitors or similar industrial processes. These values should be extracted from publicly available performance reports and sustainability disclosures of market-leading companies recognised for their sustainability excellence [60]. Careful validation of the data source and contextual alignment with the assessed processes is essential to ensure credibility. Where industrial competitor data are limited or inaccessible, benchmarking references can alternatively be established using peer-reviewed studies and sustainability databases maintained by industry associations or international agencies [61]. If external benchmarking remains unfeasible, a final fallback is the use of internal historical data. In this case, reference points are established based on the best historical performance records available internally within the organisation or industry consortium. It is crucial to ensure that internal references are clearly documented, contextually comparable and consistently applied when conducting internal benchmarking or similarity assessments within the same operational environment.

Incorporating multiple KPI referencing pathways enhances the framework's adaptability to varying data availability. However, alternative benchmarks should be treated as indicative rather than definitive standards, and consistency must be maintained across all processes assessed. For internal benchmarking, normalisation against historical best performance may be acceptable, whereas cross-sectoral or external benchmarking requires consistent use of external BAT or industry-wide best-in-class references to avoid bias. Mixing reference types

across sectors risks distorting similarity scores and undermining the validity of sustainability assessments [62,63]. Therefore, all reference sources and justifications should be fully documented to maintain methodological transparency and reproducibility.

### 6.3.3 Normalisation and similarity assessment

To enable cross comparisons, collected raw KPI values ( $V_{raw}$ ) are normalised relative to their corresponding BAT values ( $V_{BAT}$ ). A ratio-based normalisation approach was selected to maintain consistency across diverse KPIs. Two normalisation equations (1 and 2) were utilised, depending on whether a higher KPI value indicates improved performance or the opposite.

For KPIs where higher values indicate better performance (i.e. guideword: Increase), normalisation was conducted using the formula:

$$V_{norm} = \frac{V_{raw}}{V_{BAT}} \quad (1)$$

Conversely, for KPIs where lower values are desirable (i.e. guideword: Reduce), the normalisation equation was:

$$V_{norm} = \frac{V_{BAT}}{V_{raw}} \quad (2)$$

In both normalisation approaches, a resulting normalised score ( $V_{norm}$ ) equal to 1 indicates that the process performance precisely meets the BAT benchmark. Values above 1 reflect sustainability performance superior to BAT, whereas values below 1 indicate performance inferior to BAT, thus clearly quantifying relative sustainability performance deviations. Following normalisation, process-level similarity was assessed using the Relative Percent Difference (RPD). Pairwise comparisons are conducted between all processes, resulting in structured similarity matrices. RPD quantitatively measures the relative difference between the normalised KPI values of two processes (A and B), expressed as:

$$RPD = \frac{|V_{norm.A} - V_{norm.B}|}{\frac{(V_{norm.A} + V_{norm.B})}{2}} \times 100 \quad (3)$$

Lower RPD scores indicate greater similarity between processes, signalling opportunities for effective benchmarking. Conversely, higher RPD scores highlight performance gaps, identifying priority areas for targeted sustainability improvements and strategic interventions.

#### 6.3.4 Similarity Matrix Structure

To illustrate performance similarities and differences, the SIMSA framework uses structured similarity matrices. These matrices provide a quantitative view of relative performance differences by expressing the similarity (or dissimilarity) between manufacturing processes through pairwise comparisons using RPD values. As shown in Figure 40, the matrices act as decision-support tools that highlight benchmarking priorities and opportunities for process optimisation. The SIMSA framework supports two complementary similarity matrix configurations, designed for different benchmarking objectives:

- Within-Line Similarity Matrix (Figure 40 (a)): Enables comparative assessments of processes within the same manufacturing line or sector. It facilitates internal benchmarking, identification of best practices and process optimisation opportunities.
- Cross-Line Similarity Matrix (Figure 40 (b)): Enables comparative benchmarking of processes across two distinct manufacturing lines or sectors. It helps identify opportunities for cross-sectoral benchmarking and knowledge transfer.

The dual-structure approach enhances the framework's versatility and practical utility. Users can apply these matrices to optimise internal efficiencies within one production line or to drive innovation and sustainability improvements through cross-sectoral benchmarking.

|        |        |    |    |     |    |
|--------|--------|----|----|-----|----|
| (a)    | Line A |    |    |     |    |
| Line A |        | A1 | A2 | ... | An |
|        | A1     |    |    |     |    |
|        | A2     |    |    |     |    |
|        | ...    |    |    |     |    |
|        | An     |    |    |     |    |

|        |        |    |    |     |    |
|--------|--------|----|----|-----|----|
| (b)    | Line B |    |    |     |    |
| Line A |        | B1 | B2 | ... | Bn |
|        | A1     |    |    |     |    |
|        | A2     |    |    |     |    |
|        | ...    |    |    |     |    |
|        | An     |    |    |     |    |

**Figure 40 Structure of within-line (a) and cross-line (b) similarity matrices within the SIMSA framework. Diagonal cells in the within-line matrix are greyed out as these represent identical processes, thus having a similarity score of 100% (RPD=0%). Cross-line comparisons (Line A vs. Line B) do not contain identical-process comparisons and thus all cells remain active**

### 6.3.5 Objective Multi-Level Aggregation (OSW-TOPSIS)

To aggregate similarity scores across KPIs and dimensions, it is essential to account for the relative importance of each indicator. Simply summing or averaging the scores would implicitly treat all KPIs and sustainability dimensions as equally significant, which can distort results and obscure priority areas for improvement. Weighting ensures that indicators with greater relevance or impact exert appropriate influence on the aggregated similarity scores. This study introduces a structured method termed OSW TOPSIS (Objective Simulation based Weighting with TOPSIS) to determine weights objectively (Figure 41). The method is designed to reduce subjectivity in weighting, ensure reproducibility and adapt to datasets of varying completeness and focus. OSW TOPSIS uses Monte Carlo simulation combined with gamma distributions to generate a large set of plausible weighting scenarios [64]. Weights are sampled by drawing independent gamma random variables and normalising them to sum to one, which yields a Dirichlet distribution on the simplex that is commonly used to model uncertainty in MCDA weights [65–67]. Each scenario is then evaluated with TOPSIS, and the scenario with the highest closeness to the ideal solution is selected for aggregation [68].

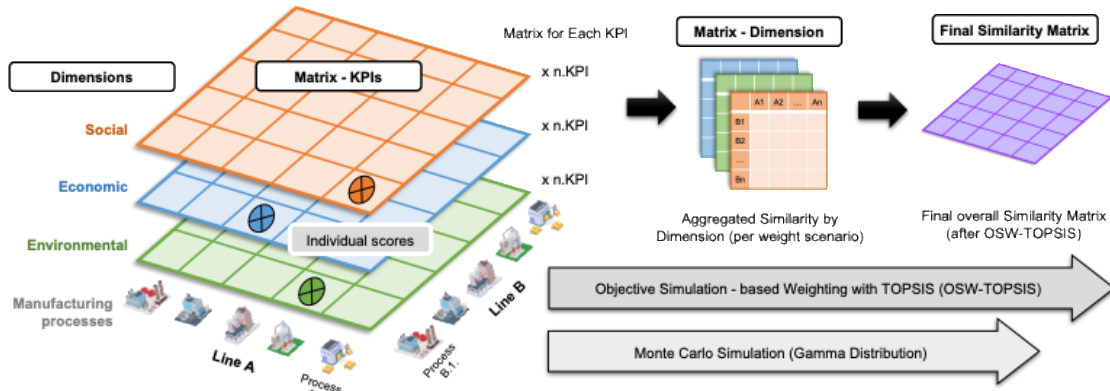


**Figure 41 Overview of the OSW-TOPSIS method. Process-level similarity scores are calculated across selected KPIs, then aggregated first at the KPI level within each dimension, and subsequently at the dimension level across multiple sustainability pillars. Weighting scenarios are generated via Monte Carlo simulation and evaluated using TOPSIS to derive the aggregated similarity matrices, culminating in a final overall similarity matrix**

The weighting is applied at two levels. At the KPI level, weights are assigned to individual KPIs within each sustainability dimension and used to aggregate KPI-level similarity matrices into dimension-level matrices. At the dimension level, weights are assigned to the three core sustainability dimensions (environmental, economic, and social) and used to produce a single overall similarity matrix. Each weighting scenario is normalised so that weights sum to one at both levels:

$$\sum_{k=1}^n W_k^{(KPI)} = 1 \quad (4)$$

$$W_{\text{environmental}} + W_{\text{economic}} + W_{\text{social}} = 1 \quad (5)$$

The normalised weights from each scenario are then applied to the relevant similarity matrices to compute a corresponding aggregated matrix.

To identify the most representative weighting configuration, TOPSIS is used to rank each scenario by comparing its aggregated similarity outcomes to a hypothetical ideal solution (minimum dissimilarity) and a negative-ideal solution (maximum dissimilarity). The closeness of each scenario to the ideal is calculated using Euclidean distance:

$$D^+ = \sqrt{\sum_{j=1}^n (V_j - V_j^{ideal})^2}, D^- = \sqrt{\sum_{j=1}^n (V_j - V_j^{negative\ ideal})^2} \quad (6)$$

$$C^* = \frac{D^-}{D^+ - D^-} \quad (7)$$

The scenario with the highest relative closeness  $C^*$  is selected, yielding an objective and balanced set of weights for final aggregation.

The Monte Carlo search is run for up to 1,000 iterations, generating a new weight vector at each step. To improve efficiency, we adopted an early-stopping rule that terminates the search when the best TOPSIS closeness score shows no improvement for a fixed number of consecutive iterations. Such patience-based termination is widely used in stochastic optimisation, while Monte Carlo simulation commonly employs stopping rules based on convergence diagnostics or precision targets [69–71]. The chosen criterion serves the same purpose as halting once additional sampling yields negligible gains. A key feature of OSW-TOPSIS is its flexibility, as users can select only a subset of KPIs within each sustainability dimension based on relevance or data availability, while the method remains methodologically consistent regardless of scope. This makes it suitable for both full-spectrum sustainability assessments and focused case studies. By combining probabilistic weighting, scenario testing and objective selection, OSW-TOPSIS provides a transparent, scalable and bias-resistant approach to sustainability similarity analysis that can be applied across sectors and use cases.

### 6.3.6 Methodological Impacts and Limitations

The SIMSA framework and its associated OSW-TOPSIS method introduce a structured, objective approach to sustainability benchmarking at the manufacturing-process level. By integrating simulation-based weighting and cross-sectoral similarity assessments, SIMSA enhances reproducibility and comparability, addressing key methodological gaps in existing sustainability evaluation practices. Through the use of Monte Carlo simulation and gamma-

distributed weight generation, OSW-TOPSIS reduces biases and the time typically associated with subjective expert weighting in conventional MCDA. This enables researchers and industrial practitioners to systematically identify targeted sustainability interventions and facilitate cross-sectoral knowledge exchange.

However, several limitations must be acknowledged. The quality of sustainability comparisons within SIMSA remains dependent on the availability and accuracy of benchmarking data, which may vary across sectors and regions. Although fallback methods are integrated to address data gaps, reliance on internal, competitor-based, or literature-derived references may introduce variability and highlight a broader gap in industrial benchmarking standards. Additionally, while the RPD-based similarity assessment captures quantitative differences effectively, it may not fully account for qualitative contextual factors such as technological maturity, regional regulatory conditions, or socio-economic impacts. RPD results should therefore be interpreted alongside qualitative insights to avoid overly narrow conclusions. Despite these limitations, the SIMSA framework offers a substantial advancement toward more objective, scalable and actionable sustainability benchmarking across several manufacturing industries.

## **6.4 Case study**

Following the development of the SIMSA framework, a case study was implemented to demonstrate its practical application and confirm its methodological capabilities. The goal is to provide a tangible example of how SIMSA can be applied to real-world manufacturing scenarios, particularly for sustainability benchmarking at the unit process level within process manufacturing industries. The scope of the study focuses on the environmental and economic dimensions, comparing manufacturing processes from two distinct production lines belonging to two different industrial sectors. Although the analysis is limited to a subset of KPIs and dimensions, it effectively illustrates the core functionalities and flexibility of the SIMSA framework, including both within-line and cross-line benchmarking, and multi-level aggregation using objective weighting. A structured set of steps was followed, which coincides with the stages

outlined in the methodology. After selecting a sector and production line, a mapping exercise took place, focusing on the relevant unit processes. This is followed by the sourcing of best-available reference values, which are used to normalise process KPI values. Finally, the similarity matrices are constructed using RPD and objective multi-level aggregation using the OSW-TOPSIS approach.

#### **6.4.1 Sector selection, process mapping and KPIs normalisation**

Unit processes were selected as the primary focus of this study because they represent the fundamental building blocks of manufacturing systems. A unit process is a distinct operation that applies a mechanical, thermal or chemical transformation to raw materials or intermediate products. Each process has defined inputs and outputs and is characterised by unique values for energy use, material efficiency, emissions and operational costs. These attributes make unit processes suitable for detailed sustainability assessments [9,72]. Within this study, two production lines were selected from different sectors to capture diversity in process types and ensure relevance across industrial contexts. The chosen sectors were steel and cement manufacturing, selected for their varied process characteristics and high environmental and energy impacts, as widely reported in the literature [73,74]. These collected processes provide the basis for conducting similarity assessments both within each production line and across sectors.

Five KPIs were used to evaluate similarity across processes, namely, electrical energy consumption, thermal energy consumption, carbon emissions, energy cost and productivity. These correspond to the environmental and economic dimensions. Benchmark reference values for each KPI were obtained primarily from authoritative sources such as EU BREFs and sector-specific best practice reports. Where direct BAT values were not available, best-in-class approximations were taken from credible secondary literature and technical references. Where process-specific data were missing, plant-level values were scaled based on the typical contribution of each process. This was mainly required for energy and emissions data. For productivity, equipment capacity

values were taken from manufacturer specifications where available; otherwise, values were taken from previous studies. Energy cost was estimated by multiplying the reference energy consumption by the lowest industrial energy tariffs in Europe. While this introduces location-based variation, it is acknowledged that energy cost can also be influenced by technological improvements such as heat recovery and on-site electricity generation [75,76]. As such, the estimated values remain practical reference points regardless of plant location.

As for the current performance data, limited access to consistent process-level information required the adoption of a hybrid data strategy. While the benchmark values were collected or estimated from literature, current performance values were simulated using direction-sensitive randomisation to reflect realistic deviations from benchmark performance. This simulation enabled the development of a consistent dataset for evaluating the similarity-based benchmarking framework across diverse scenarios. Specifically, for KPIs where lower values indicate better performance (such as energy use or emissions), BAT values were multiplied by factors ranging from 1.05 to 1.5. For KPIs where higher values are preferred (such as production throughput), multiplicative factors between 0.7 and 0.95 were applied. These randomisation ranges were informed by published performance variability observed in sustainable manufacturing benchmarking studies [9,77,78]. This approach allowed for the generation of realistic current values without relying on proprietary or incomplete datasets, while maintaining data integrity for methodological testing. Finally, all KPI values were normalised using a BAT-relative ratio-based approach described in the methodology. All collected data is provided in Table E.1 in Appendix E. The resulting normalised values formed the input for constructing similarity matrices at the indicator level to be aggregated through the SIMSA framework to support multi-dimensional similarity assessments across processes and sectors.

#### **6.4.2 Matrix Construction and OSW-TOPSIS Aggregation**

The similarity matrices were developed to assess sustainability-related differences between manufacturing processes. Five KPI-specific matrices were

created using RPD, each representing pairwise deviations in performance for a single indicator. Full KPI matrices are provided in Appendix E, Figure E-1 (a) to (e). The five matrices were grouped into two dimension-level matrices. One covered environmental indicators, and the other covered economic indicators. Aggregation was carried out using OSW-TOPSIS, which identifies the most balanced weighting scenario through simulated iterations. Figure 42 shows the resulting aggregated matrices for the environmental (a) and economic (b) dimensions.

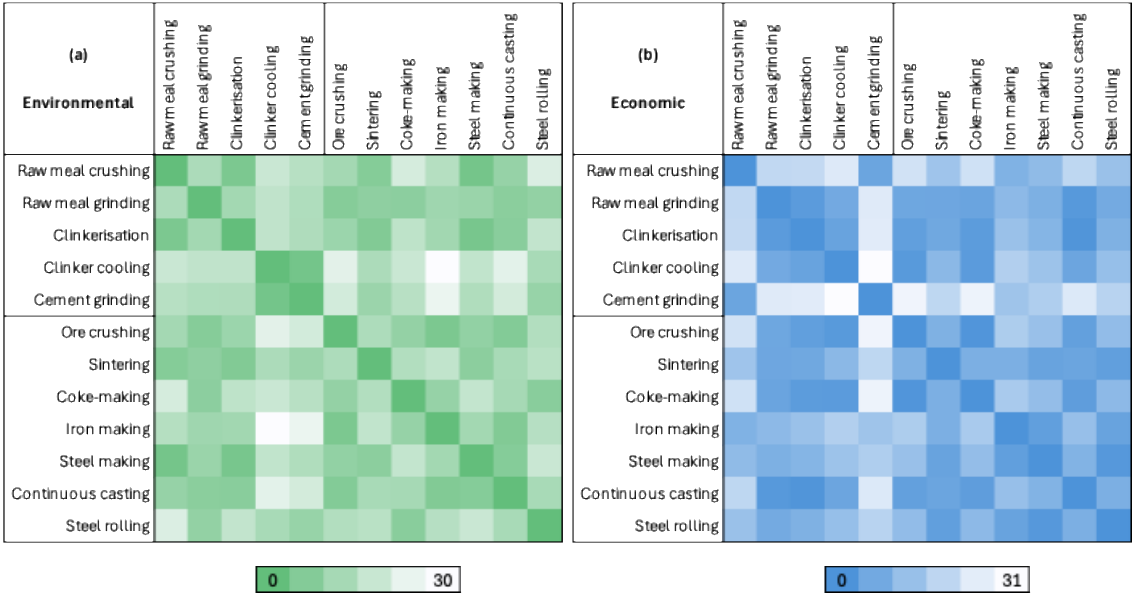


**Figure 42 Aggregated similarity matrices representing (a) environmental and (b) economic dimensions. The matrices reflect dissimilarity scores derived from the OSW-TOPSIS aggregation of KPI-level similarity matrices within each dimension**

The dimension-level matrices were further combined to produce a single overall similarity matrix, shown in Figure 43. This matrix offers a consolidated view of process similarity across all indicators. It is the main reference for subsequent benchmarking and clustering analysis.

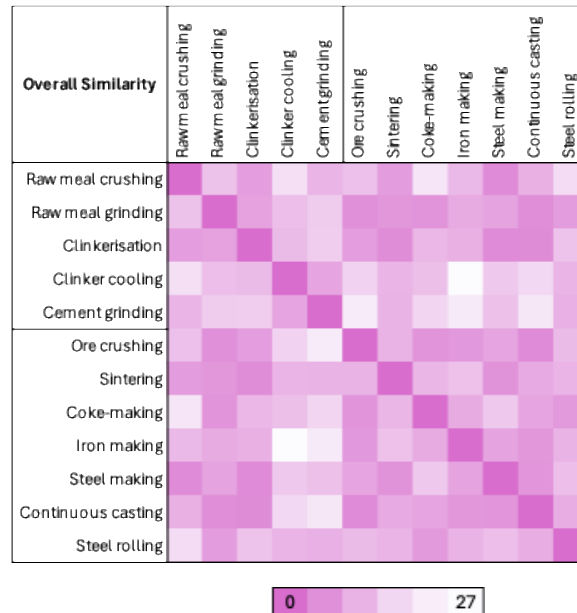


**Figure 43 Overall similarity matrix combining environmental and economic dimensions. The matrix is constructed through a second-level OSW-TOPSIS aggregation, integrating both dimension-level matrices**

RPD values and initial KPI-level matrices were produced in Excel to allow transparency and manual checks. The aggregation using OSW-TOPSIS was implemented in Python to ensure reproducibility and efficient computation. Weights and iterations are displayed in Table E.2 and Table E.3 in Appendix E.

## 6.5 Discussion

This section will discuss the results of the case study, including identified benchmarking opportunities and analysis of the patterns observed. It will also explore the implications of the findings for sustainability improvement and process optimisation in industries.

### 6.5.1 Evaluation of reproducibility

To evaluate the robustness and consistency of the OSW-TOPSIS aggregation, the full process was repeated across 20 independent runs using the original normalised data. The resulting average weights and standard deviations are visualised in Figure 44. The CO<sub>2</sub> emissions indicator received the highest weight within the environmental dimension, averaging 0.823 with relatively low variability

( $\pm 0.042$ ), indicating its strong and consistent influence on sustainability similarity patterns. Thermal and Electrical energy followed with average weights of 0.096 and 0.080, respectively. For the economic dimension, Energy Cost overwhelmingly dominated ( $0.974 \pm 0.018$ ), while Productivity remained marginal ( $0.026 \pm 0.018$ ), suggesting it played a limited role in shaping the economic similarity matrix. When aggregating to the overall matrix, the Economic dimension received a significantly higher weight ( $0.958 \pm 0.026$ ) compared to the Environmental dimension ( $0.042 \pm 0.026$ ), reinforcing the greater influence of economic performance in this case study. The narrow error bars across all indicators demonstrate strong reproducibility and support the reliability of the OSW-TOPSIS-based weighting under stochastic conditions.

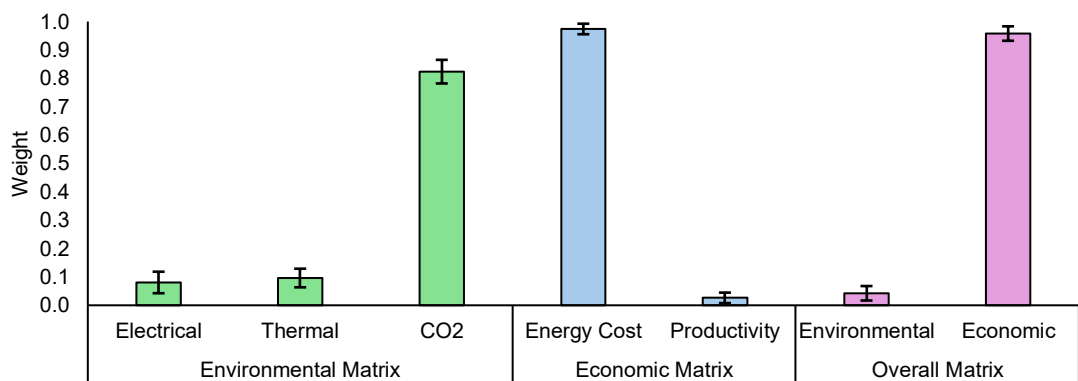


**Figure 44 Mean of weights assigned to each KPI and dimension across 20 independent OSW-TOPSIS runs. Error bars indicate the standard deviation ( $\pm 1\sigma$ ) observed across runs**

### 6.5.2 Benchmarking analysis and cross-validation

The SIMSA framework enabled a structured evaluation of sustainability performance similarities between unit processes from two distinct manufacturing sectors. Following normalisation of KPI data and matrix construction, the resulting similarity scores were analysed to identify benchmarking opportunities and validate patterns of process commonality previously reported in the literature.

To explore the alignment between functional similarity and sustainability performance, cross-validation was conducted using findings from a previous study by the author [45], which identified 18 shared or analogous operations

across process industries. Within that study, processes such as pyroprocessing, crushers and mills, and drying units were highlighted as particularly prevalent across both sectors, contributing significantly to energy use and emissions.

This case study confirms that several of those common processes also exhibit high sustainability similarity, as demonstrated by low RPD scores, as presented in Table 20. For instance, steel making and Clinkerisation were identified as shared processes and recorded a low dissimilarity score of 5.66%, suggesting strong alignment in sustainability performance across sectors. Similarly, Sintering and Clinkerisation also showed a low RPD of 6.10%, supporting the feasibility of cross-sector benchmarking and knowledge transfer for these processes. These findings reinforce the credibility of SIMSA in identifying not only functional overlap but also real performance proximity, which is critical when transferring best practices or evaluating improvement options

**Table 20 Shared Process Pairs with Low Dissimilarity (High Similarity)**

| Process A           | Process B      | Commonality Score | SIMSA RPD |
|---------------------|----------------|-------------------|-----------|
| <b>Steel making</b> | Clinkerisation | 1                 | 5.66%     |
| <b>Sintering</b>    | Clinkerisation | 1                 | 6.10%     |

Conversely, the results also highlight cases where functional similarity does not equate to sustainability similarity, as seen in Table 21. For example, cement grinding and raw meal grinding, though commonly used and functionally related, displayed a relatively high dissimilarity score of 17.79%, despite being flagged as shared processes. Likewise, cement grinding and ore crushing showed a dissimilarity of 23.57%, indicating substantial variation in performance, likely due to contextual factors such as process configuration, equipment efficiency, or integration within the production line.

**Table 21 Shared Process Pairs with High Dissimilarity**

| Process A              | Process B         | Commonality Score | SIMSA RPD |
|------------------------|-------------------|-------------------|-----------|
| <b>Cement grinding</b> | Raw meal grinding | 3                 | 17.79%    |
| <b>Ore crushing</b>    | Cement grinding   | 2                 | 23.57%    |

These contrasting cases illustrate SIMSA's ability to move beyond structural similarities and provide a quantitative foundation for benchmarking decisions. It allows users to identify which processes offer transferable sustainability practices and where improvement efforts should be context-specific. In doing so, this analysis not only supports the validity of prior mapping work but extends its usefulness by layering quantitative sustainability performance over structural similarity, offering a more nuanced approach to identifying benchmarking and knowledge exchange potential in process industries.

## **6.6 Conclusion**

This study introduced the SIMSA framework as a structured and objective approach to cross-sectoral sustainability benchmarking at the unit process level. By combining BAT-relative normalisation, pairwise process comparisons using RPD, and objective weighting through the OSW-TOPSIS method, SIMSA addresses key limitations of conventional benchmarking approaches, including sector-specific isolation, subjective weighting, and limited process-level resolution.

The case study applied across steel and cement sectors demonstrated SIMSA's ability to identify both transferable best practices and context-specific improvement needs. Processes such as steel making and clinkerisation were found to exhibit strong alignment in sustainability performance, validating previous mappings of process commonality while adding a quantitative dimension. Conversely, instances where functionally similar processes displayed significant performance differences highlighted the value of using similarity-based benchmarking to guide targeted interventions rather than relying solely on structural commonality.

Several avenues for future development have been identified to enhance the robustness and applicability of the framework. Expanding the analysis to include the social dimension will provide a more comprehensive view of sustainability performance. Automation of the workflow, from matrix construction through OSW-TOPSIS aggregation, will improve scalability and usability for industrial applications. Additionally, integrating similarity scores with process commonality

data and clustering analysis will enable more structured identification of shared improvement opportunities. Finally, exploring dynamic or context-sensitive weighting approaches could further adapt the framework to different decision-making contexts. Overall, SIMSA represents a significant step towards enabling reproducible, data-driven, and cross-sectoral sustainability benchmarking. By providing a more relational and granular understanding of process performance, it offers a practical tool for researchers, policymakers and industry stakeholders seeking to advance sustainable manufacturing and industrial cooperation.

## **6.7 Contribution of Paper to Thesis Objectives**

This paper directly contributes to Objective 5 by developing and demonstrating the SIMSA framework, a novel methodology for cross-sectoral sustainability benchmarking at the manufacturing-process level. The study introduces a structured method for comparing processes based on similarity in sustainability performance, overcoming the limitations of sector-specific benchmarks and subjective weighting. By applying ratio-based KPI normalisation relative to BAT values and using a Monte Carlo simulation with OSW-TOPSIS for objective weighting, the framework ensures robustness and adaptability across contexts.

The research provides several key contributions to the thesis. First, it advances the thesis narrative by embedding process-level sustainability assessment within a similarity-based framework, shifting the focus from isolated rankings to more flexible, cross-sector benchmarking. Second, it introduces a practical method for handling multi-criteria trade-offs, allowing for full or partial inclusion of sustainability dimensions depending on data availability and decision context.

The case study on the cement and steel sectors demonstrates the approach in practice, highlighting both transferable insights and sector-specific differences. These contributions advance the thesis ambition to deliver methods that are practical and flexible across use cases. The SIMSA framework, and its integration with earlier work on shared processes and sustainability KPIs, represents a critical step toward enabling industrial collaboration and informed sustainability efforts across foundation industries.

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## **7 Discussion**

### **7.1 Overview and Alignment with Research Aims**

This thesis aimed to address the pressing sustainability challenges faced by foundation industries, including cement, glass, ceramics, metals, paper, and chemicals. These sectors are essential to economic development yet are among the most resource- and emissions-intensive. To achieve meaningful sustainability improvements in these industries, it is crucial to implement robust methods for benchmarking and informed decision-making that go beyond broad sectoral analysis and place greater emphasis on individual manufacturing processes [1, 2].

The thesis is structured around five interconnected research objectives that create a clear and logical analytical progression. It began with a critical evaluation of existing decision-support tools and their components. Next, it developed an environmental indicators selection framework based on expert feedback and applied those indicators in process benchmarking [3, 4]. It moved on to exploring shared process structures across sectors [5]. Finally, it culminated in the development of a novel similarity-based benchmarking framework for sustainability assessment. Each chapter addresses a specific gap in the sustainability benchmarking landscape, whether in terms of methodological inconsistencies, ambiguous indicator selection, limited data comparability, or the absence of scalable tools. Together, they provide a structured and layered response to the overarching research aim of enabling informed, data-driven decision-making for sustainability transitions at the process level, both within and across the industries. The focus on unit processes enables a level of granularity that is typically absent in broader sector-wide assessments, revealing dependencies and improvement opportunities that are often overlooked [6].

At the start, Chapter 2 established the foundation by reviewing comparative decision-making tools and methods in manufacturing, guided by the PRISMA framework and analysed using NVivo. It revealed a limited emphasis on comparative process-level assessments and inconsistent integration of

sustainability metrics. These findings provided the thematic basis for the subsequent work. Chapter 3 built on this foundation by addressing the lack of structured environmental indicators at the process level [7, 8]. The developed framework offers a practical method for identifying and prioritising environmental KPIs, based on traceability, alignment with sustainability goals, and applicability across sectors. The methodology and findings of this work supported subsequent benchmarking exercises in the thesis.

In Chapter 4, the thesis moved beyond indicator selection and adopted a systems view of manufacturing processes across the foundation industries. By mapping the factors influencing energy use through causal loop diagrams, the chapter provides an overview of the interdependencies that affect performance in these complex industrial systems. The analysis highlighted how configurations, material attributes and control mechanisms affect energy consumption. To better understand current performance, energy thresholds were established based on best practices, emerging innovations, and theoretical minimums. The gaps observed between these values indicate a global shortfall, uncovering the need for rapid and targeted improvements. The findings of this work have also facilitated the recognition of commonalities across the sectors and, therefore, initiated the subsequent studies to identify shared areas where interventions could be replicated across sectors.

To enable this, Chapter 5 introduced a structured method for evaluating commonalities among foundation industries. Using an adapted DSM, it identifies 18 shared processes and classifies them by function, outcome, and enabling technologies. This cross-sectoral mapping supports the development of transferable improvement strategies by revealing where industrial processes overlap and where coordinated improvements may be most effective.

Finally, Chapter 6 synthesised the previous insights into a unified benchmarking tool. The Similarity-based Sustainability Assessment framework (SIMSA) incorporates ratio-based normalisation, Monte Carlo-based weighting and TOPSIS ranking to enable reproducible, objective comparisons of process sustainability performance. Case studies in the steel and cement sectors

demonstrated how SIMSA enables both within-sector and cross-sector benchmarking, allowing users to identify improvement strategies based on how processes perform, rather than limiting comparisons to their respective sectors [9]. Collectively, the chapters first established theoretical groundwork, then utilised practical methodology and implementation to offer a robust and structured approach to achieving the research objectives.

## **7.2 Contribution to Knowledge**

This thesis makes several contributions to the fields of sustainable manufacturing, industrial benchmarking, and decision-support approaches. The systematic review presented in the early stages of the research offers a structured classification and appraisal of existing decision-making tools, identifying key limitations in their scalability, comparative nature and integration of sustainability considerations.

Following on, a key conceptual contribution is the development of a method for selecting environmental KPIs that balances academic insight with industrial relevance. This was achieved by extracting indicators from the literature and ensuring their practical applicability through a validated selection process. Moreover, the created causal loop diagrams introduce a systems thinking perspective to the analysis. These diagrams help to visualise interactions between process-level factors, highlighting aspects that may be overlooked in conventional benchmarking approaches, but also mutual aspects across process industries. This shifts the analysis from isolated metrics to a more holistic understanding of performance dynamics.

The thesis also offers a novel application of the dependency structure matrix, adapted to identify shared processes across different industrial sectors. This adaptation facilitates the recognition of cross-sectoral commonalities and reveals opportunities for shared sustainability improvements, strengthening the case for coordinated decarbonisation strategies. All of these elements come together in the development of SIMSA, a new framework that combines process similarity assessment with objective MCDA weighting. SIMSA incorporates Monte Carlo simulation, ratio-based normalisation, and a dual benchmarking structure to

provide a more transparent, reproducible, and scalable alternative to existing tools, many of which rely on subjective inputs or lack cross-sectoral flexibility. While the scoring aspect provided a structured way to quantify process similarity across indicators, the weighting aspect ensured that more influential KPIs and dimensions appropriately shaped the final assessment, reflecting their relative importance in sustainability performance.

Fundamentally, the work repositions sustainability benchmarking as a process-level activity rather than one constrained by plant or sector boundaries, regardless of the benchmarking purpose or scope. On the inherently trade-off-based scale of information precision and information life proposed by Miller et al. [10], the SIMSA framework demonstrated the ability to balance the analytical precision of functional benchmarking by operating at the unit process level, while also extending the relevance and usability of the results to broader strategic contexts, as illustrated in Figure 45.

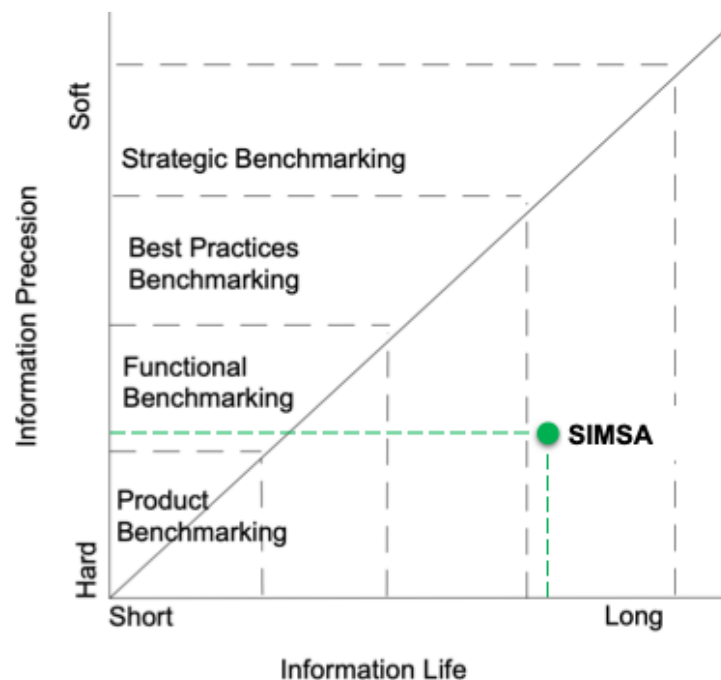


**Figure 45 The positioning of the SIMSA framework across the precision versus life of benchmarking information scale, adapted from [10]**

Together, these contributions offer a clearer and more actionable basis for assessing and improving sustainability where decisions are most often made.

They also expand the methodological and conceptual toolkit available to researchers and practitioners, enabling more targeted, transferable, and effective approaches to sustainability in industrial systems.

### **7.3 Limitations and Future Research Directions**

While this research introduces several effective tools and methods, it is important to acknowledge its limitations, many of which also inform directions for future work. The benchmarking and similarity analyses relied on datasets of varying quality and completeness. In several instances, assumptions or interpolations were required to maintain comparability, particularly due to the lack of comprehensive process-level best practice data across sectors. In terms of scope, some components, such as the KPI framework, prioritised the environmental dimension. Although the approach is intended to be transferable to economic and social indicators, this transferability was not fully demonstrated. Given that sustainability is inherently multidimensional, future work should focus on integrating and validating all three pillars to support a more comprehensive assessment. Moreover, some case studies focused on a limited subset of foundation industries. While these demonstrations effectively showcased the methods' capabilities, broader application and validation across additional sectors would be necessary to further ascertain their adaptability and robustness. These limitations highlight the need for a structured approach for collecting and organising best practices that align with all sustainability dimensions, are adaptable across sectors, and explicitly account for trade-offs.

Additional opportunities for advancement include applying SIMSA within the context of industrial symbiosis. Doing so could uncover shared resource efficiencies and support coordinated decarbonisation strategies. Expanding the framework to include upstream and downstream life cycle stages would also offer a more complete view of sustainability performance, aligning the methodology more closely with life cycle thinking. From a usability standpoint, developing automated and interactive visualisation platforms would enhance the accessibility of the tool, which could support more intuitive interpretation of benchmarking results and streamline the identification of improvement opportunities. Finally, the

framework would benefit from further industrial case studies using real data across all sectors and sustainability dimensions. These extensions would improve the scalability, inclusivity, and practical relevance of the methodology, increasing its value to both academic researchers and industry practitioners.

## 8 Conclusion

This thesis developed a structured approach to sustainability benchmarking that repositioned the process level as the central unit of analysis. By shifting the focus away from sector-wide averages and plant-level aggregates, it enabled a more precise identification of performance variations and shared inefficiencies across foundation industries. This perspective deepened the understanding of sustainability dynamics and supported the design of more targeted and transferable improvement strategies.

The research began with a systematic literature review, guided by the PRISMA framework and supported by thematic analysis using NVivo. This approach highlighted variations in decision-support approaches and revealed key limitations that informed the subsequent work. After examining how different industries interpret KPIs and the inconsistencies in their application, a framework for environmental KPI selection was developed based on a review of academic literature and expert validation to reflect industrial needs. To address the complexity of industrial systems, causal loop diagrams were used to visualise feedback mechanisms that influence energy use. These diagrams enhance quantitative indicators by providing insights into performance drivers. Furthermore, shared manufacturing processes were mapped using an adapted Dependency Structure Matrix, which offered a structured of cross-sectoral functional overlaps and highlighted opportunities for coordinated improvement. Finally, the development of the SIMSA framework integrated these elements into a cohesive decision-support framework. Through the use of Monte Carlo simulations, SIMSA generated objective weightings for sustainability indicators without relying on subjective expert input. Additionally, it utilised Relative Percent Difference to evaluate performance similarity, allowing for benchmarking both within and across sectors. These aspects contributed to the tool's reproducibility and adaptability to a variety of industrial contexts.

The findings underscored the importance of process-level analysis by showing that functional commonalities and performance similarities across sectors could reveal strategic opportunities for improvement that broader classifications might

overlook. Hence, this research advanced theoretical thinking in industrial ecology, decision-making and performance optimisation. Practically, the outcomes of this work provided valuable insights to industry stakeholders. The environmental KPI set, energy maps and benchmarking thresholds enabled explicit performance monitoring. Cross-sectoral process exploration supported shared learning and efficient resource allocation, particularly in energy-intensive operations such as milling, drying, and pyroprocessing. SIMSA provided a data-driven approach to guide operational improvements and technology adoption.

By combining conceptual development with applied methods, the thesis connected academic research and industrial relevance. It demonstrated that meaningful sustainability progress required not only robust metrics but also a shift in how performance was compared and understood across complex manufacturing systems. The research established a foundation for future work that responds to the realities of industrial interconnectedness, thereby emphasising the necessary collaborative effort required for achieving a more sustainable production.

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# Appendices

## Appendix A Ethical approval letter



2 August 2025

Dear Mr Sherif ,

Reference: CURES/26205/2025

Project ID: 28678

Title: Similarity Assessment of Manufacturing Processes Within and Across Sectors

Thank you for your application to the Cranfield University Research Ethics System (CURES).

**We are pleased to inform you your CURES application, reference CURES/26205/2025 has been reviewed. You may now proceed with the research activities you have sought approval for.**

If you have any queries, please contact CURES Support.

We wish you every success with your project.

Regards,

CURES Team

## Appendix B Chapter 2 – Paper 1

**Table B.1 Summary of the explored literature**

|    | Source | Date | Aim                                                                                     | Method                                                                              | Aspect                                                                    |
|----|--------|------|-----------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|---------------------------------------------------------------------------|
| 1  | [42]   | 2024 | Compares the sustainability of two metal AM methods                                     | A TOPSIS-based analysis was used with multiple indicators                           | Environmental and economic                                                |
| 2  | [43]   | 2022 | Develops a decision support system to select a 3D printing technology                   | An evaluation criteria list using a posteriori-based MCDA approach                  | Resource performance capabilities and manufacturing requirements          |
| 3  | [44]   | 2023 | Systematically analyses CO <sub>2</sub> capture technologies for the cement industry    | Techno-economic analysis was conducted to recommend optimal technologies using MCDA | Technical, economic, and environmental impacts                            |
| 4  | [45]   | 2020 | Proposes a method to select the best manufacturing technology based on several criteria | Uses a TOPSIS-based MCDA approach                                                   | Cost, performance, and resource availability                              |
| 5  | [46]   | 2021 | Compares EDM and laser processes for creating cooling holes in gas turbines             | Multiple MCDA methods were applied                                                  | Energy consumption, material use and process efficiency                   |
| 6  | [47]   | 2016 | Compares selective laser sintering with other AM processes                              | Direct comparison of time-cost and quality analysis of processes                    | Focuses on time, cost, and surface quality                                |
| 7  | [48]   | 2022 | Develops a multi-criteria decision support system for machining process selection       | Uses PROMETHEE multi-criteria decision-making approach                              | Economic and productivity criteria, with a focus on sustainability        |
| 8  | [49]   | 2017 | Compares traditional and AM methods in the aerospace industry                           | Applies AHP, SPA, and VDI 2225 decision-making methods                              | Production characteristics including raw materials, energy, time and cost |
| 9  | [50]   | 2015 | Proposes a new metric (OEEE) to evaluate environmental effectiveness in manufacturing   | Uses the OEEE metric to compare environmental impacts                               | Environmental sustainability and process efficiency                       |
| 10 | [51]   | 2021 | Compares finish machining and mass finishing for AM competitiveness                     | Direct comparison of surface quality                                                | Surface roughness and post-processing effectiveness                       |

|    |      |      |                                                                                                 |                                                                 |                                                             |
|----|------|------|-------------------------------------------------------------------------------------------------|-----------------------------------------------------------------|-------------------------------------------------------------|
| 11 | [52] | 2024 | Selection of a suitable AM process using a three-way decision-making model                      | TOPSIS, MOORA and VIKOR to rank AM processes                    | Mechanical properties of the product                        |
| 12 | [53] | 2016 | Tailoring soy protein film properties by selecting manufacturing processes                      | LCA to compare environmental impacts of wet and dry processes   | Environmental impacts and performance of the processes      |
| 13 | [54] | 2020 | Develops a process selection methodology based on economic and environmental performance        | Fuzzy logic and LCA                                             | Manufacturing costs and environmental trade-offs            |
| 14 | [55] | 2019 | Process and resource selection methodology in AM design                                         | AHP-based decision-making framework                             | Economic analysis and performance efficiency                |
| 15 | [56] | 2023 | Examines additive and subtractive manufacturing                                                 | LCA and LCC                                                     | Sustainability and cost-effectiveness                       |
| 16 | [57] | 2021 | Compare hybrid additive-subtractive manufacturing                                               | LCEA model using primary energy demand as the evaluation metric | Energy demand and utilisation efficiency                    |
| 17 | [58] | 2015 | Evaluate energy performance and provide improvement guidelines                                  | Energy performance benchmarking                                 | Energy performance                                          |
| 18 | [59] | 2021 | Evaluate renewable diesel production                                                            | TOPSIS analysis                                                 | Environmental impact and economic sustainability            |
| 19 | [60] | 2023 | Develops a hybrid decision-making framework for AM process selection                            | CRITIC and EDAS-based multi-criteria decision-making approach   | Surface roughness and dimensional accuracy                  |
| 20 | [61] | 2021 | Compares additive and subtractive rapid prototyping techniques                                  | AHP analysis                                                    | Surface roughness, cost and processing time                 |
| 21 | [62] | 2022 | Develops a context-based decision support system for energy-efficient manufacturing             | Monitoring and decision-support framework for energy efficiency | Impact on energy performance                                |
| 22 | [63] | 2014 | Compares fuzzy linguistic approaches for material selection in custom prosthetics manufacturing | Fuzzy AHP decision-making method                                | Material selection, custom fit and manufacturing efficiency |
| 23 | [64] | 2016 | Compares the environmental impacts of additive versus traditional manufacturing technologies    | Environmental impact comparison using LCA tools                 | Relative environmental impact of processes                  |

|    |      |      |                                                                                                      |                                                                                                |                                                                        |
|----|------|------|------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------|------------------------------------------------------------------------|
| 24 | [65] | 2020 | Presents an MCDA approach for AM process selection                                                   | MCDM approach based on process performance assessment                                          | Process performance and efficiency                                     |
| 25 | [66] | 2020 | Develops a decision support system for selecting AM processes based on benchmarking                  | Benchmarking and decision-support system                                                       | Performance benchmarking and process selection in AM                   |
| 26 | [67] | 2022 | Develops a multi-criteria decision-making method for AM process selection                            | MCDA tool with scenario analysis                                                               | Evaluates process performance across different manufacturing scenarios |
| 27 | [68] | 2023 | Presents fuzzy-based models for the classification of machining and production data                  | Fuzzy logic-based classification method                                                        | Data ambiguity reduction in machining and production processes         |
| 28 | [69] | 2023 | Develops a framework for selecting materials and manufacturing technologies                          | SAW, TOPSIS and PROMETHEE were used                                                            | Material and manufacturing process performance                         |
| 29 | [70] | 2021 | Assesses the utility of owning versus outsourcing 3D printing jobs                                   | Estimated utilisation factor and fuzzy sets                                                    | Cost, tardiness, energy and waste                                      |
| 30 | [71] | 2019 | Develops an online decision-support tool for selecting technology in biopharmaceutical manufacturing | Decision-support tool based on an aggregated score from a set of indicators                    | Economic, environmental, social and quality metrics                    |
| 31 | [72] | 2019 | Assess environmental performance in cooling tower operations                                         | A scenario-based approach using best-case and worst-case analyses based on a set of indicators | Efficiency, environmental, energy and economic performance             |
| 32 | [73] | 2023 | Develops an advanced process for Lean manufacturing approach                                         | Developed an integrated MCDA-VSM model                                                         | Environmental sustainability and process efficiency indicators         |
| 33 | [74] | 2020 | Conducts an environmental analysis of selective laser melting in AM                                  | LCA for evaluating environmental impacts                                                       | Environmental performance                                              |
| 34 | [75] | 2022 | Proposes a system model for robust tablet manufacturing process selection                            | Computational simulation for process modelling                                                 | Process efficiency and product quality                                 |
| 35 | [76] | 2020 | Selects the best green manufacturing process for oil production                                      | AHP method is used to perform an evaluation of pairwise comparisons                            | Environmental sustainability, economic performance and availability    |

|    |      |      |                                                                                                    |                              |                                              |
|----|------|------|----------------------------------------------------------------------------------------------------|------------------------------|----------------------------------------------|
| 36 | [77] | 2023 | Develops a decision support system for selecting robust manufacturing processes in food processing | MCDA approach                | Process reliability and food safety          |
| 37 | [78] | 2024 | Evaluates the environmental footprint of additive and subtractive manufacturing processes          | LCA and process benchmarking | Environmental impact and resource efficiency |

## Appendix C Chapter 3 – Papers 2 and 3

### C.1 Paper 2

Table C.1 Full set of criteria

|            |                |              |
|------------|----------------|--------------|
| Accurate   | Automated      | Complete     |
| Actionable | Buy-in         | Documented   |
| Aligned    | Comparable     | Inexpensive  |
| Timely     | Understandable | Standardised |
| Trackable  | Valid          | Unambiguous  |
| Predictive | Quantifiable   | Relevant     |

## C.2 Paper 3

**Table C.2 The collected metrics and the categorisation exercise performed as a part of the study to create initial knowledge database. Total number of metrics collected: 147, after removing duplicates: 111**

| Input                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                               |                                                                                                                                                       |            | Operations                                                                                                                                                                                                                                                                                                                                                                       |            |            | Output                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                |                                                                                                                                                                                                                                      |            | Level                                                  |
|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------|------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------|------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------|--------------------------------------------------------|
| Reduce                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                              | substitute                                                                                                                                            | compensate | Reduce                                                                                                                                                                                                                                                                                                                                                                           | substitute | compensate | Reduce                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                | substitute                                                                                                                                                                                                                           | compensate |                                                        |
| Energy consumption<br>Fuel consumption<br>Material consumption<br>Water utilization<br>Resource consumption<br>Resource productivity<br>water consumption<br>Materials and Packaging<br>Non-renewable energy<br>Electricity consumption on maintenance<br>Energy consumption for transportation<br>Mass of disposed consumables<br>Unwanted output<br>Percentage of reusable/recycled material<br>carbon footprint<br>electricity consumption<br>gas consumption rate<br>Transportation electricity consumption<br>Transportation fossil fuel consumption<br>Fossil fuel consumption on maintenance | Renewable Energy<br>reused materials<br>remanufactured materials<br>Usage of renewable material<br>Renewable electricity<br>Water reuse rate          | -          | Global Warming Potential<br>Acidification Potential<br>Resource intensity<br>Depletion of fossil fuel potential<br>Depletion of mineral resources potential<br>Climate change potential<br>Ozone depletion potential<br>Human toxicity potential<br>Photochemical ozone creation potential<br>Water depletion potential<br>Environmental impact<br>Transportation<br>Maintenance | -          | -          | Waste Management<br>Noise pollution<br>Nonproduct output<br>Waste potential<br>Output intensity<br>Hazardous waste<br>Inert and non-inert waste<br>Atmospheric emissions<br>Disposed Waste<br>Gas emissions<br>waste energy<br>Noise Pollution<br>ozone-depleting gases<br>overall material consumption<br>Valuable resources<br>Mass of restricted material in disposed packaging<br>Emission to water<br>Emission to land<br>Emission to air<br>emission of ozone-depleting substance rate<br>waste reduction rate                                                                                                                                                                                                                                                                                                                                                                                                  | Use of renewables<br>Renewable material<br>Consumables reuse ratio (%)<br>Ratio of recycled chips and scraps (%)<br>Recycling of solid waste<br>Percentage Of Reusable/Recycled Material<br>Percentage Of Waste Recycled Off/On Site | -          | <b>Facility</b><br>Includes Scores 1, 2 and 3          |
| In-line energy consumption<br>In-line electricity consumption<br>In-line fossil fuel consumption                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                    | Renewable Energy<br>reused materials<br>remanufactured materials<br>Usage of renewable material<br>renewable electric source rate<br>Water reuse rate | -          | Global Warming Potential<br>Acidification Potential<br>Resource intensity<br>Depletion of fossil fuel potential<br>Depletion of mineral resources potential<br>Climate change potential<br>Ozone depletion potential<br>Human toxicity potential<br>Photochemical ozone creation potential<br>Water depletion potential<br>Environmental impact                                  | -          | -          | Hazardous waste<br>Inert and non-inert waste<br>Emission of wastewater<br>waste energy<br>Mass of disposed consumables<br>Green House Gases (GHG)<br>GHG emission from energy consumption of the line                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                 | Use of renewables<br>Renewable material<br>Consumables reuse ratio (%)<br>Ratio of recycled chips and scraps (%)<br>Recycling of solid waste<br>Percentage Of Reusable/Recycled Material<br>Percentage Of Waste Recycled Off/On Site | -          | <b>Multi-process system</b><br>Includes Scores 1 and 2 |
| Energy consumption<br>Fuel consumption<br>Material consumption<br>Water utilization<br>Resource consumption<br>Resource productivity<br>water consumption<br>Raw material usage<br>Restricted Material<br>Resource efficiency<br>Energy efficiency<br>Waste use efficiency<br>virgin material consumption<br>recycled material consumption<br>Non-renewable material<br>carbon footprint<br>electricity consumption<br>gas consumption rate<br>Energy efficiency                                                                                                                                    | Renewable Energy<br>reused materials<br>remanufactured materials<br>Usage of renewable material<br>renewable electric source rate<br>Water reuse rate | -          | Global Warming Potential<br>Acidification Potential<br>Resource intensity<br>Depletion of fossil fuel potential<br>Depletion of mineral resources potential<br>Climate change potential<br>Ozone depletion potential<br>Human toxicity potential<br>Photochemical ozone creation potential<br>Water depletion potential                                                          | -          | -          | Hazardous waste<br>Inert and non-inert waste<br>Emission of wastewater<br>waste energy<br>Mass of disposed consumables<br>Carbon dioxide (CO2)<br>Mass of restricted disposals<br>Mass of mist generation<br>Carbon monoxide (CO)<br>Methane (CH4)<br>Sulphur dioxide (SO2)<br>Nitrogen oxide (NOx)<br>oxygen demand<br>Phosphorus (PO4)<br>Ammonia (NH3)<br>Solid waste<br>Chemical waste<br>hazardous substances<br>Mass of disposed chips and scraps<br>Mass of restricted materials in disposed consumables<br>Mass of restricted material in disposed raw materials<br>Mass of restricted material in scrap parts going to landfill<br>Mass of non-collected solid wastes<br>Mass of non-collected liquid wastes<br>Mass of non-collected gaseous wastes<br>Mass of solid wastes going to landfill<br>Mass of liquid waste disposed<br>Solid waste generation<br>Percentage Of Waste Generated Per Product Units | Use of renewables<br>Renewable material<br>Consumables reuse ratio (%)<br>Ratio of recycled chips and scraps (%)<br>Recycling of solid waste<br>Percentage Of Reusable/Recycled Material<br>Percentage Of Waste Recycled Off/On Site | -          | <b>Unit process</b><br>Includes Scope 1                |

## Appendix D Chapter 5 – Paper 6

**Table D.1 Classification of the identified processes**

|    | Process            | Concept                        | Outcome                           | Machinery                  |
|----|--------------------|--------------------------------|-----------------------------------|----------------------------|
| 1  | Ore crushing       | Size reduction                 | Reduction in particle size        | Crusher                    |
| 2  | Raw meal crushing  | Size reduction                 | Reduction in particle size        | Grinding mills, ball mills |
| 3  | Ceramic crushing   | Size reduction                 | Reduction in particle size        | Crusher                    |
| 4  | Cullet crushing    | Size reduction                 | Reduction in particle size        | Crusher                    |
| 5  | Raw meal grinding  | Size reduction                 | Reduction in particle size        | Crusher                    |
| 6  | Cement grinding    | Size reduction                 | Reduction in particle size        | Grinding mills, ball mills |
| 7  | Chopping           | Size reduction                 | Reduction in particle size        | Chipper                    |
| 8  | Iron making        | Pyroprocessing (reduction)     | Molten product                    | Blast furnace              |
| 9  | Steelmaking        | Pyroprocessing (oxidation)     | Molten product                    | Basic oxygen furnace       |
| 10 | Sintering          | Pyroprocessing (Solid-state)   | Agglomeration of ores             | Sinter strand              |
| 11 | Coke-making        | Pyroprocessing (decomposition) | Decomposition of raw materials    | Coke oven                  |
| 12 | Clinkerisation     | Pyroprocessing (Solid state)   | Sintering of intermediate product | Rotary kilns               |
| 13 | ceramic firing     | Pyroprocessing                 | Sintering and densification       | Furnace                    |
| 14 | Steam cracking     | Pyroprocessing (pyrolysis)     | Decomposition of raw materials    | Cracker furnace            |
| 15 | Glass melting      | Pyroprocessing                 | Molten product                    | Furnace                    |
| 16 | Spray drying       | Moisture removal               | Dry Intermediate product          | Spray dryer                |
| 17 | Ceramic drying     | Moisture removal               | Dry Intermediate product          | Dryers                     |
| 18 | Paper drying       | Moisture removal               | Dry Intermediate product          | Steam dryer                |
| 19 | Ceramic moulding   | Shaping                        | Formation of shape                | Pressing machines          |
| 20 | Glass moulding     | Shaping                        | Formation of shape                | Moulding machine           |
| 21 | Hot rolling        | Shaping                        | Plastic deformation               | Rolling mill               |
| 22 | Clinker cooling    | Temperature reduction          | Cooling of intermediate product   | Air coolers                |
| 23 | Paper forming      | Forming                        | Formation of shape                | Fourdrinier                |
| 24 | Calendaring        | Forming                        | Sheet formation                   | Calendars                  |
| 25 | Quenching          | Temperature reduction          | Gas stabilisation                 | Heat exchangers            |
| 26 | Extrusion          | Forming                        | Pelletised product                | Extruder                   |
| 27 | Annealing          | Temperature reduction          | Strengthened product              | Lehr oven                  |
| 28 | De-barking         | Surface treatment              | Decontaminated raw material       | Drum debarker              |
| 29 | Coating            | Surface treatment              | Hardened product                  | Sprayer                    |
| 30 | Continuous casting | Solidification                 | Solidified product                | Ladle, tundish, mould      |

|    |                |                        |                                  |                        |
|----|----------------|------------------------|----------------------------------|------------------------|
| 31 | Glazing        | Surface coating        | Decorated layer                  | Printers               |
| 32 | Pulp making    | Delignification        | Processed intermediate product   | Cooking digester       |
| 33 | Compression    | Pressurisation         | Increase pressure                | Compressors            |
| 34 | Fractionation  | Co-products separation | Isolation of individual products | Fractionating columns  |
| 35 | Polymerisation | Radical polymerisation | Polymer formation                | Polymerisation reactor |
| 36 | Degassing      | Degasification         | Quality enhancement              | Degasser               |
| 37 | Glass mixing   | Homogenisation         | Raw material mixture             | Blender                |

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## Appendix E Chapter 6 – Paper 7

### E.1 References and Current Processes Data

**Table E.1** Collected and estimated reference values and the simulated current values used for the similarity analysis. Data for the cement sector compiled from [1-8], the steel from [9-16] and the energy cost estimation from [17-22]

| Sector | Process            | Electrical Energy (kWh/t) |         | Thermal Energy (GJ/t) |         | CO <sub>2</sub> Emissions (kg CO <sub>2</sub> /t) |         | Energy Cost €/ton |         | Productivity (ton/hour) |         |
|--------|--------------------|---------------------------|---------|-----------------------|---------|---------------------------------------------------|---------|-------------------|---------|-------------------------|---------|
|        |                    | Reference                 | Current | Reference             | Current | Reference                                         | Current | Reference         | Current | Reference               | Current |
| Cement | Raw meal crushing  | 30                        | 44.35   | 0                     | 0.00    | 12                                                | 16.80   | 2.40              | 3.40    | 1600                    | 1180.00 |
|        | Raw meal grinding  | 27                        | 32.50   | 0                     | 0.00    | 12                                                | 15.00   | 2.16              | 2.50    | 200                     | 188.00  |
|        | Clinkerisation     | 2                         | 2.85    | 2.9                   | 3.75    | 790                                               | 1070.00 | 10.08             | 11.50   | 200                     | 160.00  |
|        | Clinker cooling    | 23                        | 32.45   | 0                     | 0.00    | 0                                                 | 0.00    | 1.84              | 2.00    | 200                     | 167.00  |
|        | Cement grinding    | 45                        | 63.60   | 0                     | 0.00    | 23                                                | 24.50   | 3.60              | 5.40    | 150                     | 110.00  |
| Steel  | Ore crushing       | 30                        | 33.69   | 0                     | 0.00    | 4                                                 | 5.40    | 2.40              | 2.65    | 1800                    | 1350.00 |
|        | Sintering          | 28                        | 40.93   | 1.37                  | 1.50    | 200                                               | 252.00  | 6.93              | 8.40    | 450                     | 335.00  |
|        | Coke-making        | 28                        | 30.80   | 3.82                  | 4.80    | 794                                               | 935.00  | 15.30             | 17.00   | 1.2                     | 0.93    |
|        | Iron making        | 25                        | 26.63   | 12.85                 | 17.70   | 1219                                              | 1670.00 | 45.95             | 60.00   | 200                     | 184.00  |
|        | Steel making       | 25                        | 34.37   | -0.26                 | 0.00    | 282                                               | 390.00  | 1.11              | 1.40    | 400                     | 347.00  |
|        | Continuous casting | 8                         | 9.73    | 0.03                  | 0.04    | 88                                                | 122.00  | 0.74              | 0.85    | 70                      | 55.00   |
|        | Steel rolling      | 90                        | 107.24  | 1.54                  | 2.12    | 82                                                | 90.00   | 12.47             | 15.50   | 75                      | 67.50   |

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E.2 Matrices

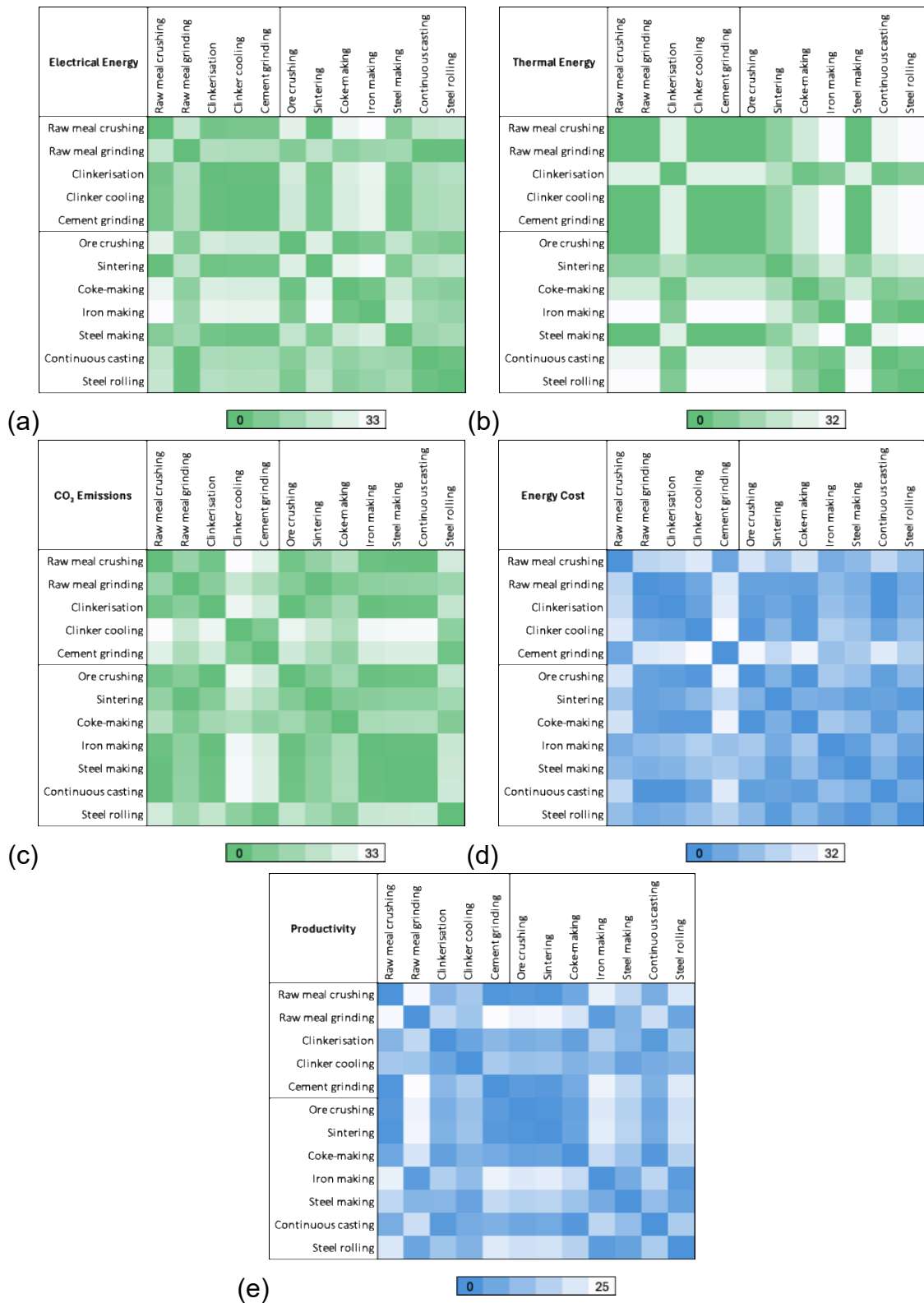


Figure E-1 KPI level matrices for (a) Thermal Energy, (b) Electrical Energy, (c) CO<sub>2</sub> Emissions, (d) Energy Cost and (e) Productivity

**Table E.2 Dimension-level matrices aggregation data**

| Dimension     | KPI           | Weights | Iterations |
|---------------|---------------|---------|------------|
| Environmental | Electrical    | 0.395   | 313        |
|               | Thermal       | 0.064   |            |
|               | CO2 Emissions | 0.541   |            |
| Economic      | Energy Cost   | 0.935   | 169        |
|               | Productivity  | 0.065   |            |

**Table E.3 Overall matrix aggregation data**

| Overall Matrix | Environmental | Economic | Iterations | Best C*  |
|----------------|---------------|----------|------------|----------|
|                | 0.736         | 0.264    | 193        | 0.616265 |